Do Telework Locations Influence Subjective Well-Being : A Latent Class Cluster Analysis of Post-Pandemic Data in the Netherlands

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SHORT SUMMARY

This study investigates the relationship between various telework locations (i.e., work from home, work during travel and work elsewhere) and subjective well-being in the post-pandemic era using data from the Netherlands Mobility Panel. Six types of teleworkers were identified through latent class cluster analysis: 'home-dominant teleworkers,' 'multi-location teleworkers,' 'multi-location and travel-enabled workers,' 'office-dominant teleworkers with limited flexibility,' 'field-based teleworkers,' and 'office-dominant teleworkers with travel-enabled productivity'. However, non-significant differences in well-being across clusters suggest that providing support for work from home, work during travel, and other flexible arrangements are all crucial for policymakers and companies during the transition to telework.

Keywords: Telework; Subjective Well-being; Latent Class Analysis; Post COVID-19.

INTRODUCTION

Telework[1] has existed since the 1970s (Nilles, 1975) and gained popularity due to information and communications technologies (ICTs) allowing employees to work from any location. COVID-19 further promoted this trend. Policymakers support remote work to mitigate traffic congestion, improve work-life balance and employees' well-being. To do so, they have invested considerable efforts, such as establishing guidelines to ensure efficient and equitable telework. However, employers have different attitudes towards telework due to concerns about productivity and collaboration. For both policymakers and employers, understanding the impact of telework on employees' subjective well-being plays a crucial role in shaping their decisions.

Although sometimes used interchangeably, telework does not equal to work from home. After the pandemic, more people have started working from different places like cafes, libraries, co-working spaces (Ayodele et al., 2022; Hölzel and Vogl. 2023), or even while traveling. The experiences of individuals working from home may differ significantly from those working from other remote places. That is, telework locations can play a critical role in shaping its impact on subjective well-being (SWB). For example, Pabilonia & Vernon (2021) found that combining working from home with working at fixed workplaces can improve SWB by offering greater schedule flexibility, such as enabling childcare during work hours. On the other hand, working primarily from home can blur the boundaries between work and family life, reduce productivity, and limit social interaction (Mas &

[1] The definition of telework, as outlined by Mokhtarian et al. (2005), is broader than working from home and includes any work done remotely. In this study, we adopt this broader definition of "telework."

Pallais, 2020; Mokhtarian, 1991; Solís, 2017; Song & Gao, 2020). Most studies focus on the impact of working from home on people's SWB, often using data collected before or during the COVID-19 pandemic. However, telework has undergone a structural transformation since the pandemic, with workers no longer limiting themselves to home as the sole work hub. This calls for a renewed examination of telework's effects on well-being in the post-pandemic era, where flexible and diverse telework locations are increasingly the norm.

A recent study by Maheshwari et al. (2024) used post-COVID-19 data (collected in July 2022) to analyze changes in commuting and telework patterns. The study focused on how different work-from-home frequencies affect SWB. It found that teleworkers who worked from home 2–3 days per week had the highest levels of SWB, while those working from home less than once or only once per week had the lowest levels. However, the study did not explore the possibility of teleworking from other remote working locations or while traveling.

To address these gaps, our study aims to identify and empirically assess how locations of telework influences SWB. Data to estimate such influence are drawn from the Netherlands Mobility Panel 2022 to provide insights for long-term remote working policies. Additionally, our study expands the existing literature by exploring a wider range of telework locations —fixed workplaces, other remote locations, and while traveling) — to better understand their effects on SWB.

METHODOLOGY

Datasets

Data for this study were obtained from the Netherlands Mobility Panel (MPN), an annual household survey established by the Netherlands Institute for Transport Policy Analysis to investigate short-term and long-term travel patterns. The survey is conducted for 8 weeks, from September to November each year (Hoogendoorn-Lanser et al., 2015). Since 2013, household members aged 12 years and older have been invited to participate, with additional members recruited annually to account for participant attrition and ensure the sample remains nationally representative. The MPN collects a wide range of variables, including respondent characteristics (e.g., socio-demographic details, household composition, car ownership), mobility-related behaviours (e.g., commute mode choice, frequency of travel modes), and telework practices (e.g., frequency, attitudes and satisfaction) based on the participants' experiences over the past 24 months.

The main aim of this paper is to explore how various telework configurations influence individuals' SWB after COVID-19. Therefore, this study uses data from the 2022 wave of the MPN, as it captures changes following COVID-19. Specifically, after a year of strict work-from-home policies in 2021, people in the Netherlands were given more freedom in 2022 to choose their working locations as COVID-19 restrictions were lifted (Business Traveller, 2022).

Data Filtering

The data are filtered to include respondents' experiences in various telework practices. Respondents needed to complete all surveys about their telework practices and SWB status (4068, 89.2%) and need to be employed (2092, 51.5%). Being employed (paid), in our definition, means that a respondent has a job (either self-employed or employed by a company).

We define a teleworker as a worker who has teleworked at least once in a recent week. A non-teleworker is someone who has not teleworked in a recent week at all in MPN 2022 (908 respondents). In total, 1125 respondents have teleworked in 2022 in the Netherlands, which is 56.7% of the working population in the sample, higher share of workers who have teleworked during the pandemic (Sostero et al., 2020).

Latent Class Cluster Analysis

How telework experience influences SWB is explored by clustering people with various telework configurations. To achieve this, a latent class cluster analysis (LCCA) using Latent Gold software (Vermunt & Magidson, 2005) is applied to identify individuals with various telework configurations. LCCA has been widely used in previous research to classify mobility patterns (Molin et al., 2016; Ton et al., 2019). It effectively identifies unobserved subgroups within the population, capturing heterogeneity in telework experiences.

Three indicators are used to identify groups with different telework configurations as listed in **Table 1**. To ensure the accuracy of the "work during travel" measure, individuals employed in the "storage and transport" sector (52 respondents) were excluded from the analysis, as their job roles inherently involve work-related travel. The mathematical formulation of the model (Vermunt & Magidson, 2013) and its graphical visulisation are presented as follows:

$$P(y_i|z_i^{cov}) = \sum_{x=1}^{K} P(x|z_i^{cov}) \prod_{m=1}^{M} f(y_{im}|x)$$

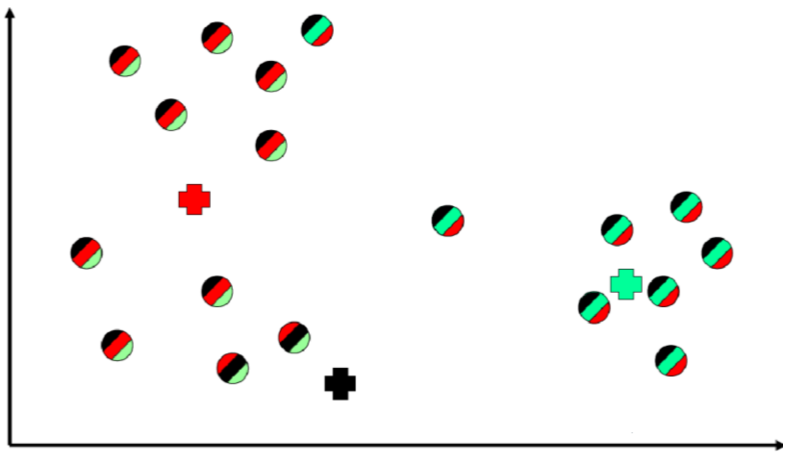

Figure 1. Graphical visualisation of latent class cluster model

Where x represents the latent variable classes based on observed indicator variables and covariates, y_{im} denotes the observed indicators, and zi^{cov} refers to covariates for individual i. The first component of the model, $P(y_i|z_i^{cov})$, represents the probability of an individual belonging to a specific class based on their covariates. The second component, $f(y_{im}|x)$, assumes conditional independence of the indicators given the latent variable, allowing the model to focus on shared class-specific patterns. As illustrated in **Figure 1**, data points (represented as pie charts) are probabilistically assigned to clusters, with each segment of the pie indicating the likelihood of belonging to a particular class. Such assignment is determined by their characteristics are represented by the active covariates z_i (the set of covariates for individual i). Distinct clusters, represented by centroids (e.g., red and cyan crosses), are formed based on these probabilities. Inactive covariates are introduced into the model only after a baseline model without covariates is identified as providing a good fit. Models with active covariates are evaluated using the R-squared statistic, a variance-based measure indicating how much of the variation in class membership can be explained by the covariates included (Magidson, 1981). In this study, total working hours and self-reported SWB are included as an inactive covariate. This approach helps explore the relationship between the identified latent classes and SWB.

Eight models were tested using LCCA to identify telework configurations, with clusters ranging from 1 to 8. The appropriate number of latent classes is determined by balancing statistical criteria and model interpretability. **Appendix A1** shows the results for all models.

RESULTS AND DISCUSSION

Descriptive characteristics

The descriptive statistics of indicators and inactive covariates are summarised in **Table 1**. Among telework indicators, hours spent at a permanent workplace (Mean = 17.25, SD = 11.76) and at home (Mean = 14.16, SD = 11.46) dominate, collectively accounting for most total working hours. The high variability in both these categories, with maximum values reaching 80 and 100 hours respectively, indicates substantial heterogeneity in work arrangements. In contrast, hours worked elsewhere (Mean = 3.95, SD = 8.78) and while traveling (Mean = 0.47, SD = 1.98) are much lower.

Regarding the inactive covariates, the total number of weekly working hours averages 35.84 (SD = 8.92), indicating a balanced workload for most respondents, but the range of 2 to 100 hours highlights a few outliers who either work minimally or have extreme work commitments. The SWB level, assessed via the Satisfaction with Life Scale (SWLS), averages 5.04 (SD = 1.04) on a 1-7 scale, reflecting generally high life satisfaction.

Table 1. Key indicators and inactive covariates and their values

Indicators	Mean	SD	Min	Max
Number of hours working at permanent workplace address during a recent week	17.25	11.76	0	80
Number of hours working at home during a recent week	14.16	11.46	0	100
Number of hours working elsewhere in a recent week	3.95	8.78	0	50
Number of hours working while travelling during a recent week	0.47	1.98	0	32
Inactive Covariates				
Number of working hours per week during a recent week	35.84	8.92	2	100
Subjective well-being level	5.04	1.04	1	7
1. SWLS - In most cases, my life is almost perfect				
2. SWLS - My living conditions are excellent				
3. SWLS - I am satisfied with life				
4. SWLS - So far I have achieved the most important things in my life				
5. SWLS - If I could start my life all over again, I would change almost nothing				

Note:
1. Min = Minimum value; Max = Maximum value; SD = Standard deviation.
2. The average of each indicator relevant to SWB is calculated to represent its level, which ranges from 1 to 7, with higher values indicating greater life satisfaction.

Classification of teleworker types

The 6-cluster model was chosen as the optimal solution (LL = -7874.0, BIC = 16120.4, classification error = 0.0204). It provides the best balance between model fit, classification quality, and interpretability, with all clusters having meaningful proportions (smallest cluster = 2.98%), making it suitable for practical application. The profiles of six classes of telework configurations are shown in **Table 2**, explained below, and thoroughly examined in terms of SWB in the following subsection.

Cluster 1. Home-dominant teleworkers. This cluster represents a large group (63.48%) with a balanced distribution between fixed workplace and home-based work. Individuals work an average of 18.2 hours per week at a fixed workplace and 17.2 hours from home. Notably, this cluster does not work at other locations or during travel. This cluster average's total weekly working hours is 35.4, suggesting a balanced yet slightly lower workload compared to other clusters. This pattern indicates a work style where the home functions as the primary hub for telework, complemented by consistent time at the permanent office. The absence of work from other locations or travel suggests a structured and stable work routine.

Cluster 2. Multi-Location teleworkers. Cluster 2 (13.56%) works an average of 36.7 hours weekly. Their work is distributed across multiple locations, with 13.6 hours at a fixed workplace, 12.0 hours working from home and 12.1 hours at alternative locations. Specially, there is no reported work time during travel for this cluster. This group exemplifies complex telework configurations that involve multiple workspaces, indicating high spatial flexibility of their work activities.

Cluster 3. Multi-location and travel-enabled workers. Cluster 3 includes 8.02% of the population. Respondents in this cluster work at diverse locations including also during travel. They work an average of 16.8 hours per week from home and 13.4 hours at their permanent workplace address, indicating a balanced distribution between remote and on-site work. Additionally, they spend an average of 4.1 hours working elsewhere, such as in co-working spaces or client locations, suggesting further flexibility in their work arrangements. This cluster also includes a small proportion of time spent working while travelling, averaging 3.4 hours per week, which implies the capacity for professional productivity during transit.

Cluster 4. Office-dominant teleworkers with limited flexibility. This cluster (6.57%) is characterized by a strong reliance on fixed workplace environments, with an average of 29.6 hours per week spent at a permanent office location (the highest among all clusters). They occasionally work from alternative locations, such as cafes or co-working spaces (on average 3.8 hours per week). Their work engagement at home and during travel is minimal, very low average working hours at home (2.1 hours per week) and no working during travel.

Cluster 5. Field-based teleworkers. Cluster 5 (5.39%) has significant engagement in offsite work environments combined with minimal home-based work and workplace-based work. Individuals in this cluster spend an average of 31.6 hours working in non-permanent locations, such as client sites, co-working spaces, or temporary offices, emphasising a mobile work style. They work 13.9 hours per week at their permanent workplace address. In contrast, this cluster does not engage in work during travel. Their weekly working hours average 32.6, which is comparatively lower than some other clusters. This work pattern suggests a focus on field-based roles or project-oriented tasks requiring a presence at multiple worksites.

Cluster 6. Office-dominant teleworkers with travel-enabled productivity. Cluster 6 represents the smallest segment (2.98%). This group works an average of 28.4 hours per week at fixed workplace. Compared to Cluster 4, besides occasionally work from home and other locations, they perform substantial amount of work during travel (6.6, the longest among the clusters). While fixed workplaces remain their primary work environment (28.4 hours per week), they also show a relatively high tendency to work from other locations, averaging 5.7 hours per week. Like Cluster 4, Cluster 6 spends minimal time working from home (1.7 hours per week), indicating a preference for workspaces outside the home environment. This group work on average more than the other clusters (42.4 hours per week).

Table 2. Profiles of each telework configuration

	Cluster1: Home-dominant teleworkers	Cluster 2: Multi-Location teleworkers	Cluster 3: Multi-location and travel-enabled workers	Cluster 4: Office-dominant teleworkers with limited flexibility	Cluster 5: Field-based teleworkers	Cluster 6: Office-dominant teleworkers with travel-enabled productivity
Cluster Size	63.48%	13.56%	8.02%	6.57%	5.39%	2.98%
Indicators						
Number of hours working at permanent workplace address during a recent week						
Mean	18.2	13.6	13.4	29.6	0.1	28.4
Number of hours working at home during a recent week						
Mean	17.2	12.0	16.8	2.1	0.9	1.7
Number of hours working elsewhere in a recent week						
Mean	0.0	11.1	4.1	3.8	31.6	5.7
Number of hours working while travelling during a recent week						
Mean	0.0	0.0	3.4	0.0	0.0	6.6
Inactive covariate						
Number of working hours during a recent week						
Mean	35.4	36.7	37.8	35.4	32.6	42.4
Subjective well-being						
Mean	5.0	5.2	5.1	5.1	5.0	5.1

How telework locations influence subjective well-being?

Table 3 and **Figure 2** depict the SWB scores of six clusters, illustrating that most clusters concentrate in the "4.5-7" score range. Clusters 2, 4 and 5 are characterised by the highest proportions in this range, reflecting a strong concentration of respondents with very high SWB. Cluster 3 displays a balanced distribution, with notable percentages in the "3.5-4.5" and "4.5-7" ranges, suggesting moderate satisfaction with some variability. Cluster 1 has a more diverse profile, with smaller peaks in these ranges, reflecting a mix of moderate and high satisfaction. In contrast, Cluster 6 is more varied, with notable proportions across all ranges, including higher presence in the "1.0-2.5" and "2.5-3.5" ranges, indicating lower well-being for some individuals.

Overall, **Figure 2** highlights that while most clusters peak in the "4.5-7" range, Clusters 2, 4 and 5 stand out for their concentrations of very high SWB, whereas Cluster 6 reflects greater variability and includes individuals with lower levels of life satisfaction.

To explore whether the satisfaction differ among people with various telework configurations, we conducted the analysis of variance (ANOVA) test. The results indicate that there are no statistically significant differences in average SWB scores across the clusters ($F = 1.049$, $p = 0.387$). Additionally, the Chi-Square test for the distribution of SWB across the six clusters resulted in a test statistic of $\chi^2=17.19$ with a p-value of 0.308, indicating no significant difference in the distribution of SWB scores across the clusters. The non-significant differences in SWB across the five clusters, defined solely by variations in telework configurations, suggest that telework configurations alone may not be a primary determinant of life satisfaction. This lack of variation could reflect individuals' adaptation to different telework conditions over time, reducing their impact on well-being. To gain a clearer understanding of how telework configurations influence SWB, the next step involves examining additional variables such as socio-demographic characteristics, job autonomy, workload, and personal attitudes for telework.

Table 3. Subjective well-being levels of five clusters

	Cluster1: Home-dominant teleworkers	Cluster 2: Multi-Location teleworkers	Cluster 3: Multi-location and travel-enabled workers	Cluster 4: Office-dominant teleworkers with limited flexibility	Cluster 5: Field-based teleworkers	Cluster 6: Office-dominant teleworkers with travel-enabled productivity
Cluster Size	63.48%	13.56%	8.02%	6.57%	5.39%	2.98%
Subjective well-being						
1.0-2.5	2.93%	1.35%	0.00%	3.85%	1.64%	4.88%
2.5-3.5	5.73%	2.70%	8.64%	6.41%	8.20%	7.32%
3.5-4.5	18.99%	17.57%	18.52%	8.97%	9.84%	14.63%
4.5-7	72.35%	78.38%	72.84%	80.77%	80.33%	73.17%
Mean	5.0	5.2	5.1	5.1	5.0	5.1

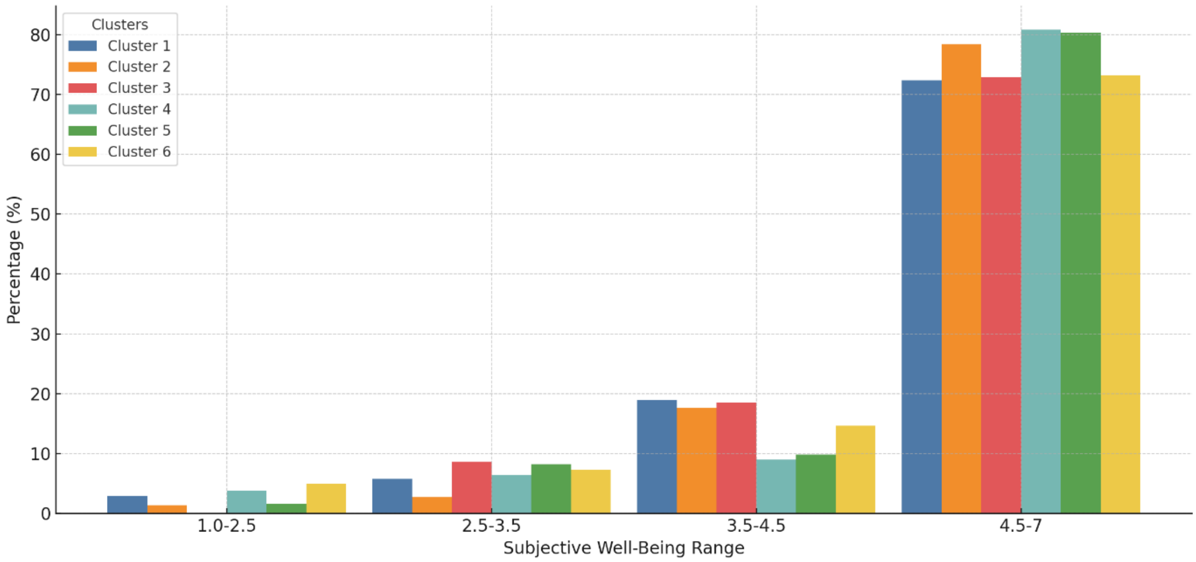

Figure 2. Comparison of subjective well-being scores across six clusters.

CONCLUSIONS

Telework has become increasingly popular after COVID-19, and workers adopt different configurations of telework, distributed across work from home, work during travel and work at other non-work locations (such as cafes and libraries). The impact of these configurations on subjective well-being has not been sufficiently studied before. Using data from the Netherlands Mobility Panel 2022, this study examines the relationship between various telework configurations and subjective well-being in the post-pandemic era. Through latent class cluster analysis, five distinct types of teleworkers are identified: home-dominant teleworkers,' 'multi-location teleworkers,' 'multi-location and travel-enabled workers,' 'office-dominant teleworkers with limited flexibility,' 'field-based teleworkers,' and 'office-dominant teleworkers with travel-enabled productivity'. However, non-significant differences in well-being across clusters suggest that telework configurations alone may not be key determinants of life satisfaction, potentially reflecting individuals' adaptation to telework conditions over time. This also implies that providing support for work from home, work during travel, and other flexible arrangements are all crucial for policymakers and companies. Employees' satisfaction can be improved regardless of the specific telework configuration.

APPENDIX A1

Table A1. Evaluation criteria to determine the optimal number of clusters based on indicators

# Clusters	LL	BIC(LL)	Npar	Classification Error	# significant BVRs
1	-15113.4	30283.1	8	0.0000	2
2	-10212.5	20544.5	17	0.0016	2
3	-8828.3	17839.3	26	0.0039	3
4	-8393.7	17033.3	35	0.0042	4
5	-8202.0	16713.2	44	0.0195	3
6	**-7874.0**	**16120.4**	**53**	**0.0204**	**3**
7	-7714.9	15865.3	62	0.0236	4
8	-7563.9	15626.7	71	0.0245	4

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