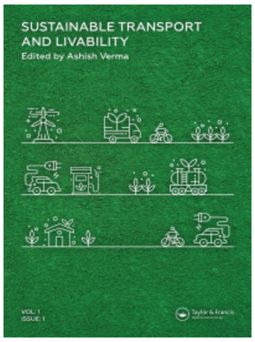


Sustainable Transport and Livability

ISSN: (Print) (Online) Journal homepage: www.tandfonline.com/journals/tstl20

Teleworkers and physical commuters during the COVID-19 pandemic: the change in mobility related attitudes and the intention to telecommute in the future

Andrea L. Hauslbauer, Jai Malik, Giovanni Circella, Xiatian Iogansen & Tibor Petzoldt

To cite this article: Andrea L. Hauslbauer, Jai Malik, Giovanni Circella, Xiatian Iogansen & Tibor Petzoldt (2025) Teleworkers and physical commuters during the COVID-19 pandemic: the change in mobility related attitudes and the intention to telecommute in the future, Sustainable Transport and Livability, 2:1, 2486800, DOI: 10.1080/29941849.2025.2486800

To link to this article: https://doi.org/10.1080/29941849.2025.2486800

Published online: 22 Apr 2025.

SUSTAINABLE TRANSPORT AND LIVABILITY
2025, VOL. 2, NO. 1, 2486800
https://doi.org/10.1080/29941849.2025.2486800

Taylor & Francis
Taylor & Francis Group

RESEARCH ARTICLE

OPEN ACCESS

Check for updates

Teleworkers and physical commuters during the COVID-19 pandemic: the change in mobility related attitudes and the intention to telecommute in the future

Andrea L. Hauslbauer[a#], Jai Malik[b‡], Giovanni Circella[b,c], Xiatian Iogansen[b] and Tibor Petzoldt[a]

[a]Institute of Transport Planning and Road Traffic, Chair of Traffic and Transportation Psychology, Technische Universität Dresden, Dresden, Germany; [b]Institute of Transportation Studies, University of California, Davis, CA, USA; [c]Department of Geography, Ghent University, Ghent, Belgium

ABSTRACT

The COVID-19 pandemic has disrupted commuting habits, with many individuals shifting to telecommuting. This study examines the impact of disrupted commuting habits on psychological constructs, such as attitudes or active lifestyle. Using longitudinal survey data from the California panel study of emerging transportation, the study compares two groups (those who started telecommuting, $N = 458$, and those who continued physically commuting, $N = 523$) at two points (early pandemic 2020 and later pandemic 2021). Exploratory factor analysis was used to extract the latent psychological constructs and structural equation modeling was used to model the intention to telecommute in the future for each year. Results show that some psychological constructs (such as attitude toward sustainable modes) remain stable across groups and time, while others (such as concern about pathogens) depend on both group and stage of the pandemic. The intention to telecommute in the future remains high and is mainly dependent on individuals' attitude toward it and their tech-savviness, rather than on a concern about pathogens or demographics. The findings may inform policies that promote sustainable and flexible mobility options, like telecommuting, that have the potential to enhance work-life balance in a post-pandemic world.

ARTICLE HISTORY Received 13 September 2024; Accepted 24 March 2025

KEYWORDS Attitudes; telecommuting; hybrid work; mobility; work-life-balance

CONTACT Andrea Lucia Hauslbauer andrea.hauslbauer@dlr.de German Aerospace Center (DLR), Institute of Transport Research, Rudower Chaussee 7, 12489 Berlin, Germany
[#]Institute of Transport Research, German Aerospace Center (DLR), Berlin, Germany.
[‡]The World Bank, Washington, DC, USA.

1. Introduction

1.1. Theoretical background

United States workers spend an average of 55.2 minutes commuting per day. In large metropolitan areas in California (e.g., Los Angeles or San Francisco), the average commuting time even exceeds one hour (Burd et al., 2021). This not only consumes significant time but also has implications for land use, sustainability, and well-being. Among United States commuters, 75.9% drive alone in motorized cars (Burd et al., 2021), occupying valuable space that could be used for pedestrians, bikes, or urban landscaping. Commuting is a major cause of greenhouse gas emissions (Kissinger & Reznik, 2019) due to the dependence on car travel, the frequency of commuting trips, and the intensity of travel during peak hours, often generating massive congestion levels on the road network. Additionally, commuting can cause negative emotions such as stress and frustration, which can spill over into the workplace and impact mood and performance (Chatterjee et al., 2020). Efforts to reclaim land from parked cars (e.g. Copenhagenize Design Co, 2024; San Francisco Smart City Challenge, 2016) and promote sustainable commuting practices (Hauslbauer et al., 2022) are on the rise, as the negative impacts of commuting by car are increasingly recognized.

In early 2020, society experienced a forceful disturbance of commuting behaviors as one of many disruptions brought about by the outbreak of the COVID-19 pandemic (Marsden et al., 2020). While the long-term effect of COVID-19 on commuting behavior is still unclear, a large body of research has dealt with the immediate changes in mobility behavior that the pandemic has led to (e.g. Anke et al., 2021; Borkowski et al., 2021; Engle et al., 2020; Matson et al., 2021; Warren & Skillman, 2020). These studies focused on, for example, the adaptations in activity patterns, mode choice, or destination choice. One particularly consistent finding is that a large part of the population that previously commuted shifted to working from home. Another part of the population continued to commute either by choice or because the nature of their work demanded physical presence (Iogansen et al., 2022).

It is unclear how the disruption in commuting habits caused by COVID-19 has affected psychological factors, such as perceptions, attitudes, and preferences toward different modes of transportation. Investigating psychological factors in transportation is essential, because they impact mobility choices and behavior (Hauslbauer, 2023; Schlag et al., 2007). For example, one crucial factor that influences mobility choices such as commuting is an individual's attitude, which refers to their learned tendency to judge certain objects or behaviors as favorable or unfavorable (Rose & Brown, 2021), and to adjust their behavior accordingly (Hauslbauer, 2023; Moody & Zhao, 2020; Steg, 2005). The theory of planned behavior (Ajzen, 1991) posits that beliefs about the outcome of a behavior result in an attitude towards it, which predicts an individual's intention to perform that behavior. For instance, attitudes toward transport modes such as toward the car or bike predict mode use (Moody & Zhao, 2020; Steg, 2005), and the consequentially sought out experiences create a feedback loop back to the behavioral beliefs, reinforcing or reshaping them. Thus, attitudes and behavior can be conceptualized in a bidirectional relationship. A bidirectional relationship between attitudes and behavior in the mobility context, specifically, has been supported using the theory of planned behavior and the theory of cognitive dissonance (Kroesen et al., 2017).

Understanding psychological factors is key to identifying approaches to adjust behaviors within the mobility system, including daily commuting (Hauslbauer, 2023). However, despite an abundance of research on altering mobility behavior, effecting lasting change is difficult. One reason for this is that mobility behavior is often mediated by habits (Aarts & Dijksterhuis, 2000), particularly the daily commute, due to the unchanging cue to "go to work" (Zarabi et al., 2019). Merely a discontinuation of exposure to cues typically fails to produce lasting behavior changes (Gardner, 2015). Instead, key life events that alter an individual's context offer important opportunities for habit inactivation (Brette et al., 2014).

The COVID-19 pandemic has disrupted commuting habits on an unprecedented scale, particularly for those who shifted to telecommuting.

The aim of this paper is twofold: we aim to (i) provide insights into the effects of the pandemic-induced habit break by exploring the differences in psychological factors between individuals who shifted to telecommuting and those who continued to commute physically at different stages of the pandemic, and (ii) develop a model that considers these psychographic factors, in order to assess how prevalent full or partial telecommuting (i.e., hybrid work) will become beyond the pandemic and how attitudes may drive this trend.

Therefore, this paper addresses a critical gap by examining how this shift has impacted mobility-related psychological factors, such as attitudes toward transportation modes. By comparing telecommuters with those who continued to commute physically, the study uses this unique context to gain insights, with physical commuters serving as a control group.

To achieve the objectives, we derived hypotheses from the theoretical background below, compared a California sample of telecommuters to physical commuters, and built a model to predict individuals' intention to telecommute in the future.

1.2. Conceptual framework and hypotheses

For this study, the above-mentioned research aims were formalized as research questions and arranged within the conceptual framework visualized in Figure 1.

i. How do mobility-related psychological factors, such as attitudes, differ between those who continued to commute physically during the pandemic and those who started to telecommute?

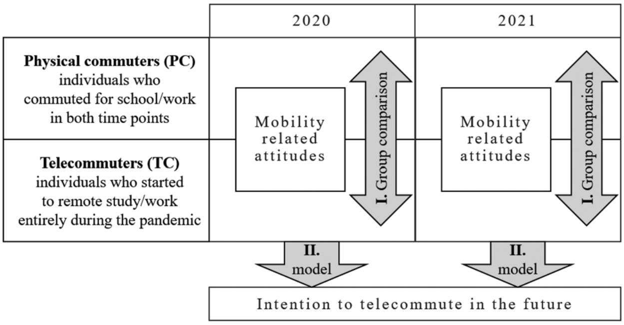


Figure 1. Conceptual framework.
Note. This figure represents the conceptual framework, outlining the research questions and subsequent analysis steps. The gray arrows visualize the research questions: (I) shows that two groups, PC and TC, will be compared in terms of their mobility-related attitudes. This comparison will be conducted for two distinct years, 2020 and 2021; (II) Two separate models will be constructed for each year. Both of these models will predict the extent to which individuals from both groups intend to telecommute in the future.

Table 1. Hypotheses derived from literature review.

Related research question		Hypothesis
I	H1	*From 2020 to 2021, the telecommuters developed a more positive attitude toward an active lifestyle than physical commuters.*
I	H2	*The telecommuters report a higher concern about pathogens than the physical commuters*
II	H3	*Concern about pathogens is positively associated with attitude toward telecommuting and the group (telecommuters)*
I	H4	*The telecommuters report a more positive attitude toward telecommuting than the physical commuters*
II	H5	*Attitude toward telecommuting is positively associated with intention to telecommute in the future and the group (telecommuters)*
II	H6	*Tech-savviness is positively associated with intention to telecommute in the future and attitude toward telecommuting*
II	H7	*The number of days the job allows telecommuting during the pandemic is positively associated with the intention to telecommute in the future, the group (telecommuters), and the attitude toward telecommuting*
II	H8	*The telecommuters show a stronger intention to telecommute in the future than the physical commuters*

ii. How do psychological and external factors influence individuals' intentions to telecommute in the distant future, and how does this influence differ between early (2020) and later stages of the pandemic (2021)?

In the following paragraphs, we describe how the reviewed literature lead to our hypotheses, which may be found in Table 1. In the text, the hypothesis numbers are indicated in brackets.

1.2.1. Socio-demographic differences

The literature highlights a socio-economic divide between telecommuters and physical commuters in both North America and Europe, as evidenced by studies

(Budnitz et al., 2020; López Soler et al., 2021; Su et al., 2021; Yasenov, 2020). These references collectively demonstrate that telecommuters typically have higher household incomes, greater levels of education, and are more frequently in professional or managerial roles. In contrast, blue-collar workers, who usually require on-site presence, are less likely to telecommute. Additionally, these studies indicate that men are more likely to telecommute than women. However, Mokhtarian and Salomon (Mokhtarian & Salomon, 1997) argued that socio-economic and demographic factors alone do not fully explain telecommuting preferences, as they can have different effects on different individuals, depending on attitudes.

1.2.2. Differences in various psychological factors

1.2.2.1. Active lifestyle. Research suggests that active mobility and round trips, such as walking and biking tours, have gained popularity amidst the pandemic (de Haas et al., 2020). It is likely that individuals who have transitioned to telecommuting have utilized this newfound time to engage in other activities which fill their daily travel time budget (Ahmed & Stopher, 2014). It seems fair to assume that telecommuting has lifted people's attitude toward an active lifestyle.

1.2.2.2. Concern about pathogens. Multiple studies have examined the public's perception of risk associated with transit or shared vehicles since the onset of the pandemic, revealing that these concerns were particularly high during the initial stages of the pandemic (Przybylowski et al., 2021; Scorrano & Danielis, 2021). It appears likely that the fear of contracting pathogens may have influenced people's decision to switch to telecommuting during the pandemic, with those who expressed higher levels of concern being more inclined to opt for telework at the onset of the pandemic. Furthermore, these individuals may also be more likely to continue telecommuting in the future.

1.2.2.3. Attitudes toward telecommuting. Chai et al. (Chai et al., 2023) identified that attitudes toward telecommuting emerged as the most significant predictor for an individual's intention to telecommute during the pandemic. However, the items of their study lean toward what we called concern about pathogens. To predict an individual's intention to telecommute beyond the pandemic, it seems crucial to extract their attitude toward telecommuting using a definition that aligns with the theory of planned behavior (Ajzen, 1991): in terms of belief of a favorable or unfavorable outcome. This includes examining beliefs about the practicality, efficiency, and overall work performance associated with telecommuting. Furthermore, following the logic of the theory of cognitive dissonance (Festinger, 1962), it seems plausible that individuals who were initially compelled to telecommute may have adjusted their attitude towards it to alleviate any cognitive dissonance.

1.2.2.4. Tech-savviness. For an individual to engage in telecommuting, they must be able to effectively use relevant information and communication technologies (ICTs), such as cloud solutions and video conference systems. The degree to which one can comfortably and competently operate ICTs has been termed “tech-savviness” among other labels. The perceived ease of use and usefulness of technology have been used as predictors for an individual’s attitude towards telecommuting and, indirectly, for their intention to continue telecommuting (Chai et al., 2023). Tech-savvy individuals are presumed to be more comfortable with utilizing ICTs at home and require less support from colleagues. Therefore, measuring an individual’s comfort with technology may represent a valuable predictor for their intention to telecommute in the future.

1.2.3. External factors for telecommuting

To create an accurate prediction model, it is important to also consider external factors that may affect telecommuting, as the option to work remotely is not always unconstrained. For instance, the extent to which the job allows teleworking likely is a crucial external factor [H7], and individuals who were initially required to work remotely during the pandemic may be more likely to continue doing so in the post-pandemic period (Rose & Brown, 2021). Thus, the commute status during the pandemic could also potentially serve as a predictor of intention to telecommute in the future [H8].

Summarizing the hypotheses of research aim II, we derive the following model (Figure 2), which will be tested for both the data of the year 2020 and 2021.

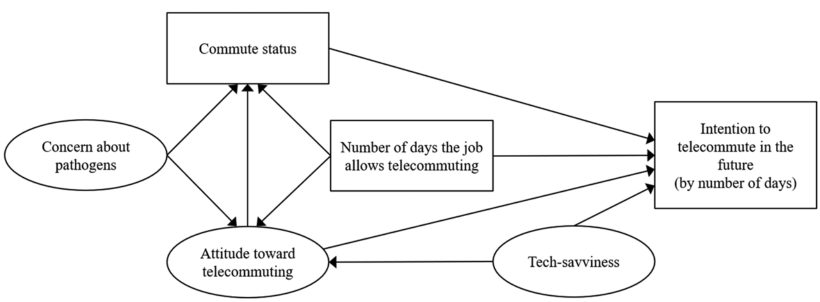


Figure 2. Hypothesized model.

2. Materials and methods

2.1. Data collection and sample

This study uses longitudinal survey data collected by researchers at the University of California, Davis, as part of a larger research effort on understanding mobility patterns during the COVID-19 pandemic (Circella et al., 2023; UC Davis Mobility Study, 2024). Four survey waves were conducted in the US, Canada, and internationally in spring 2020 (n = 13,658), fall 2020 (n = 7,983), fall 2021 (n = 14,084), and fall 2023 (n = 6,469). Data collection employed mixed sampling methods, including online panels, professional listservs, social media, and re-contacting previous participants. The surveys, conducted via Qualtrics in English and Spanish, took 30-40 minutes to complete. Data was collected on attitudes, demographics, household composition, work status, and commuting/teleworking frequency before and during the pandemic.

This present study focuses specifically on the longitudinal respondents from the State of California who participated in both fall 2020 and fall 2021 surveys. The fall 2020 survey captured individuals' attitudes and behavior earlier in the pandemic with much more restricted "stay-at-home" orders, while in fall 2021 fewer pandemic related restrictions were in place and vaccines had become available.

To address our research questions, we identified two groups in the fall 2020 survey based on their reported student/work status and commuting/teleworking frequency before and during the pandemic (Appendix A). Group 1 (PC) consists of physical commuters (*N* = 1,343, 34%) who commuted for school/work at any point, including hybrid workers. Group 2 (TC) consists of full telecommuters (*N* = 854, 21%) who switched from entirely in-person work in 2019 to fully remote in fall 2020. Of these, 981 participants also completed the fall 2021 survey, forming the final sample. Although the study mirrors demographic data (Circella et al., 2019, pp. 8–10), reliance on opinion panels means it is not a truly random sample, and the focus on two subgroups necessitates deliberate non-representativeness (Richiardi et al., 2013).

2.2. Data description

Socio-demographic data collected included age, gender, income, education, household size, presence of children, and job telecommuting eligibility (Table 2). Psychographic data were gathered using 41 Likert-scale statements, where participants indicated their agreement from "Strongly Disagree" to "Strongly Agree" (Table 3). These statements were used to create latent attitudinal constructs for analysis. The dependent variable, "intention to telecommute in the future," measured both exclusive and hybrid telecommuting. Participants selected preferred telework days post-pandemic, with responses coded for analysis. Details on survey items and their coding are in Appendix B.

Table 2. Socio-demographic data and differences between the physical commuters (PC) and telecommuters (TC).

	Group 1 (PC)	Group 2 (TC)	Total	Mann-Whitney U Test
N (commute status)	523 (53.3%)	458 (46.7%)	981	
Age in years *Mean (SD)*	46.84 (12.54)	46.41 (13.41)	46.62 (12.95)	U = .116721, $p = .491$
Gender: female *Frequency (%)*	286 (55.00%)	270 (59.21%)	556 (56.7%)	U = 114611, $p = .176$
Household income *Scale 1-7, Mean (SD)*	3.99 (1.55)	4.41 (1.48)	4.19 (1.53)	U = 83641, $p < .001$
Educational background *Scale 1-6, Mean (SD)*	4.09 (0.98)	4.29 (0.87)	4.18 (0.93)	U = 104563, $p < .001$
Household size *Mean (SD)*	2.72 (1.41)	2.59 (1.37)	2.66 (1.39)	U = 106813, $p = .125$
Children in household <18 years *Mean (SD)*	0.62 (1.01)	0.50 (0.92)	0.56 (0.97)	U = 104973, $p = .015$
Max. frequency of job allowing telework *(0 'never' - 5 '5 or more per week'), Mean (SD)*	1.75 (1.96)	3.52 (1.82)	2.57 (2.09)	$U = 62962$, $p < .001$
Days of intended future telework *Mean (SD)*	2.13 (1.96)	3.57 (1.70)	2.80 (1.97)	$U = 70161$, $p < .001$

Note. See Appendix B for more information on the coding of household income.

2.3. Analysis

2.3.1. Socio-demographic data

In addition to descriptive statistics, socio-demographic data was analyzed for differences between the groups. To accommodate for non-parametric, continuous or near-continuous variables, Mann-Whitney U tests were used (Field, 2013).

2.3.2. Latent psychographic constructs

Exploratory factor analysis (EFA) was used on 41 items from both the 2020 and 2021 datasets to derive latent constructs. EFA is an exploratory technique that reduces data dimensionality to key factors that capture the most information (for more details, see e.g. Backhaus et al., 2016; Bartz, 2015; Field, 2013; Schendera, 2010). Direct oblimin oblique rotation was applied to allow correlation among constructs. Variables with factor loadings <.50 in either dataset were removed for comparability across years. This conservative cutoff was chosen due to the small number of items (Chatterjee et al., 2020; Copenhagenize Design Co, 2024; Kissinger & Reznik, 2019; San Francisco Smart City Challenge, 2016) per construct, ensuring a strong relationship with each factor (Wigert & Agrawal, 2022). Scale reliability was confirmed with Cronbach's α >.60 (Nunnally, 1967; Streiner, 2003) and item-total correlations >.04 (Streiner, 2003). Factor analysis quality was assessed using Field's (Field, 2013) guidelines: Kaiser-Meyer-Olkin (KMO) >0.5 for sampling adequacy, significant

Table 3. Factors, items, factor loadings, and reliability (α).

Factor	#	Item *strongly disagree (1)-strongly agree (5)*	2020		2021	
			Load-ings	*α*	*Load-ings*	*α*
Pro micro-mobility	AT33	If shared bikes and/or e-scooters were cheaper, I would use them more often	.835	.790	.831	.809
	AT34	I am interested in monthly rentals of bikes and/or e-scooters that include maintenance and theft protection	.883		.779	
	AT30	Using bikesharing/e-scooter sharing is fun	.718		.751	
	AT23	If I felt protected from car traffic, I would ride a bicycle more often	.675		.631	
	AT8	I like riding a bike	.445*		.633	
Attitude toward telecom-muting	ATC9	Working from home is not practical for me (e.g., due to lack of office devices, distractions from family members).	−.760	.743	−.738	.773
	ATC3	Working from home makes me less disciplined/self-controlled.	−.718		−.720	
	ATC5	I experience substantial gains in efficiency when working from home.	.711		.724	
	ATC1	I perform better when I interact with colleagues/co-workers in person (on site).	−.696		−.730	
	ATC8	The quality of interaction during online meetings is disappointing.	−.609		−.703	
Driving affinity	AT11	I prefer to be a driver rather than a passenger.	.877	.758	.900	.759
	AT7	I like driving a car.	.824		.830	
Concern about pathogens	AT27	I will feel uncomfortable sharing a ride with strangers (e.g. UberPOOL, Lyft Share) due to concerns about pathogens (e.g. COVID-19).	.789	.661	.765	.772
	AT28	I feel uncomfortable putting my hands on the handlebar of a shared e-bike, e-scooter, e-moped recently used by someone else.	.774		.848	
	AT24	I feel uncomfortable using public transport-tation due to concerns about pathogens (e.g., COVID-19 or other).	.749		.867	
Active lifestyle	AT5	Getting regular exercise is important to me.	.820	.675	.819	.675
	AT3	I like walking.	.812		.812	
Tech-savviness	AT18	I'll stretch my budget to buy something new and exciting.	.754	.600	.744	.630
	AT14	I like to be among the first people to have the latest technology.	.708		.757	
	AT16	Having Wi-Fi and/or good internet access on my mobile phone everywhere I go is essential to me.	.704		.712	
Pro env. friendly transport	AT6	We should raise the cost of driving to reduce the negative impacts of transportation on the environment.	.941	.772	.897	.744
	AT17	We should raise the cost of driving to pro-vide funding for better public transportation.	.916		.863	
	AT19	I always think about ways in which I can reduce my impact on the environment.	.541		.560	
Car de-pendency	AT2	My schedule makes it hard or impossible for me to use public transportation.	.865	.674	.855	.676
	AT12	Most of the time, I have no reasonable alternative to driving.	.823		.801	

*In the 2020 data, this item also loaded on the construct *active lifestyle* (.469). Details on how we addressed this are provided in section 3.3.

Bartlett's test of sphericity, and factor extraction with eigenvalues >1. Factor scores were saved using the regression method, as regression-based scores provide the most reliable and interpretable estimates (Field, 2013). These scores were used for group comparisons via multivariate analysis of variance (MANOVA) to address research question I.

2.3.3. Structural equation model

A confirmatory factor analysis (CFA) was conducted to ensure a good fit for the hypothesized measurement model, followed by structural equation modeling (SEM) for both the 2020 and 2021 datasets. To predict the intention to telecommute in the future, a two-step process involving CFA and SEM with maximum likelihood estimation was used for each dataset. To ensure data precision and maintain focus on addressing our primary research question, 72 participants were excluded due to inconsistencies between reporting telecommuting and stating their job did not allow it. These participants were part of a heterogeneous group, including those forced to telecommute despite a reported unsuitability of their job, or temporarily unemployed (see Appendix C). The final sample size was $N = 909$.

CFA assessed the validity of the measurement model by evaluating how well factors were measured by individual items, ensuring skewness and kurtosis values were within +/−2 and +/−4, respectively (Field, 2013). Construct validity was evaluated using standardized loading estimates >.70 (Appendix G4), average variance extracted (AVE) >.50, and composite reliability >.70 for convergent validity, with AVE exceeding the square of factor correlations for discriminant validity (Hair et al., 2010).

SEM examined causal relationships between factors and the outcome variable to evaluate the validity of the structural model, assessing good model fit with $\chi^{2/}$df > 2 and < 5, NFI, CFI, and TLI > .90, and RMSEA < .07 (Burghard & Dütschke, 2019; Redmond, 2000).

3. Results

3.1. Socio-demographics

Table 2 provides an overview of the demographic characteristics of the two groups, with Mann-Whitney U tests being used to identify differences. Results indicate that age, gender, and household size were similar for both physical commuters (PC) and telecommuters (TC). However, telecommuters report significantly higher income and education than physical commuters, indicating a higher socio-economic status. Moreover, telecommuters had fewer children under the age of 18 living with them, reported that their job allowed them more days to telecommute, and expressed a greater likelihood of telecommuting in the future.

3.2. Generation of constructs

Following the initial exploratory factor analysis (EFA) conducted on the 41 attitudinal items using direct oblimin oblique rotation on both the 2020 and 2021 dataset, 13 items were removed due to low factor loadings. Additionally, one construct (consisting of two items) with a low Cronbach's α, and one item with a low item-total correlation that also considerably reduced the reliability of its construct, were excluded from further analysis. The remaining 25 variables were subjected to factor analysis using direct oblimin rotation.

For both datasets, the Kaiser-Meyer-Olkin measure indicated good sampling adequacy with the general KMO as well as KMO values for individual items >.50, and Bartlett's test of sphericity was significant ($p < .01$). Eight factors were extracted with eigenvalues over Kaiser's criterion of 1 and in combination explained 64.07% and 65.97% of the variance for the 2020 and 2021 datasets, respectively. Three of the 8 constructs consist only of two items, the discussion and analysis regarding their stability is detailed in Appendix D. The factors were named after interpretation and are presented in Table 3, along with items, loadings, and reliability (Cronbach's α).

3.3. Differences in attitudinal constructs between groups and years

To address the first research question, the z-standardized, regression-based factor scores were compared across groups and years (Table 4). Spider charts were used to visualize these factor scores for both groups in 2020 and 2021 (Figure 3). MANOVA indicated a significant difference between the groups for the year 2020 ($F(8, 972) = 18.91$, $p < .001$) and for the year 2021 ($F(8, 972) = 21.038$, $p < .001$). In the case of active lifestyle, the construct does not consist of the exact same items in 2020 as in 2021. Since the interpretation of this factor would thus be biased, simple means of matching items will be used instead. The specific differences per group and construct are indicated in Figure 3, and non-standardized means of constructs are available in Appendix F. For the detailed MANOVA results, please refer to Appendix E.

Some differences between physical commuters and telecommuters in car-related attitudes remained consistent over time. Physical commuters had a stronger affinity for driving and greater car dependency, while telecommuters were more positive toward environmentally friendly transportation. Both groups had similar attitudes toward micromobility (e.g., shared bikes and e-scooters).

Some differences emerged, whereas others disappeared as time passed. In 2020, tech-savviness was similar between groups, but in 2021, telecommuters were significantly more tech-savvy. In 2020, physical commuters were less concerned about pathogens than telecommuters, but by 2021, the difference was no longer significant. A follow-up dependent sample t-test showed a general drop in pathogen concern across the sample from 2020 to 2021 ($t(980) = -15.170$, $p < 0.001$; from 3.71 ± 0.98 to 3.17 ± 1.11, on a scale from 1 to 5). Regarding active

Table 4. Factor scores of constructs for both years and groups (z-standardized, N = 981).

	Year	Physical commuters		Telecommuters	
		Mean	SD	Mean	SD
Pro micromobility	2020	0.00	1.03	0.00	0.97
	2021	−0.01	1.04	0.02	0.96
Driving affinity	2020	0.10	0.95	−0.12	1.04
	2021	0.11	0.95	−0.13	1.04
Concern about pathogens	2020	−0.07	1.05	0.08	0.94
	2021	−0.01	1.01	0.02	0.99
Tech-savviness	2020	0.02	1.04	−0.03	0.96
	2021	−0.07	1.05	0.08	0.93
Pro env. friendly transport	2020	−0.12	1.01	0.13	0.97
	2021	−0.10	1.00	0.11	0.99
Active lifestyle	2020	−0.02	1.06	0.03	0.92
	2021	0.06	1.02	−0.07	0.97
Car dependency	2020	0.15	0.97	−0.17	1.01
	2021	0.11	1.01	−0.13	0.98
Att. toward telecommuting	2020	−0.27	0.90	0.31	1.02
	2021	−0.32	0.93	0.36	0.96

lifestyle, in the 2020 data, the item "I like riding a bike" (AT8) not only loaded onto the pro-micromobility construct as expected, but also showed a notable loading on the active lifestyle construct (0.469). As a result, the composition of the active lifestyle construct in 2020 differed from that in 2021. This variation in the construct's composition warranted further analysis. To ensure comparability between the 2020 and 2021 data on active lifestyle, the item in question was excluded from this additional analysis. Consequently, it was also omitted from the interpretation of the final results for active lifestyle. One-tailed dependent-sample t-tests on the means of the remaining two items revealed that from 2020 to 2021, there was a statistically significant difference in active lifestyle for telecommuters (from 4.28 ± .71 to 4.32 ± .71; $t(385) = -1.686$, $p = .046$), but not for physical commuters (from 4.23 ± .83 to 4.22 ± .81; $t(522) = .460$, $p = .323$).

Therefore, the hypotheses can be answered as followed.

H1 *(From 2020 to 2021, the telecommuters developed a more positive attitude toward an active lifestyle than physical commuters)* was supported.

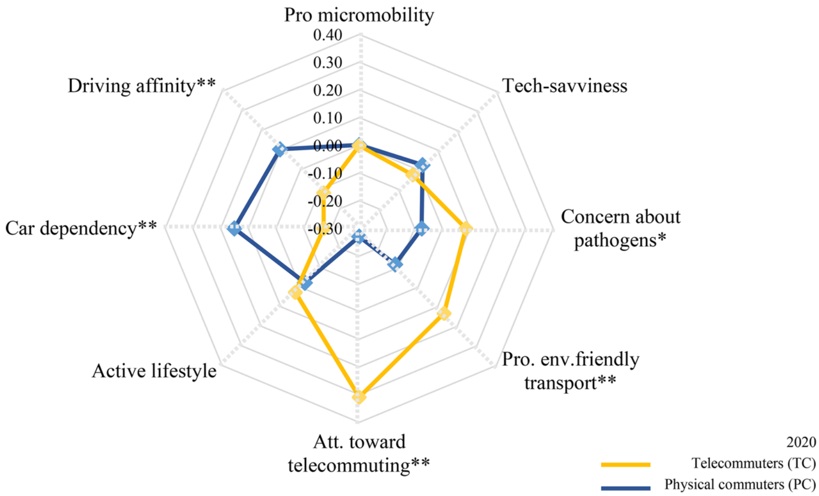
H2 (*The telecommuters report a higher concern about pathogens than the physical commuters)* was supported for the year 2020 only. In 2021, there was no difference, and overall concern dropped.

H4 (*The telecommuters report a more positive attitude toward telecommuting than the physical commuters*) was supported for both years.

3.4. Predicting the intention to telecommute in the future

3.4.1. Test of measurement model

The model included six variables: three latent constructs measured on a 1-to-5 scale - "attitude toward telecommuting" (five items), "concern about pathogens"



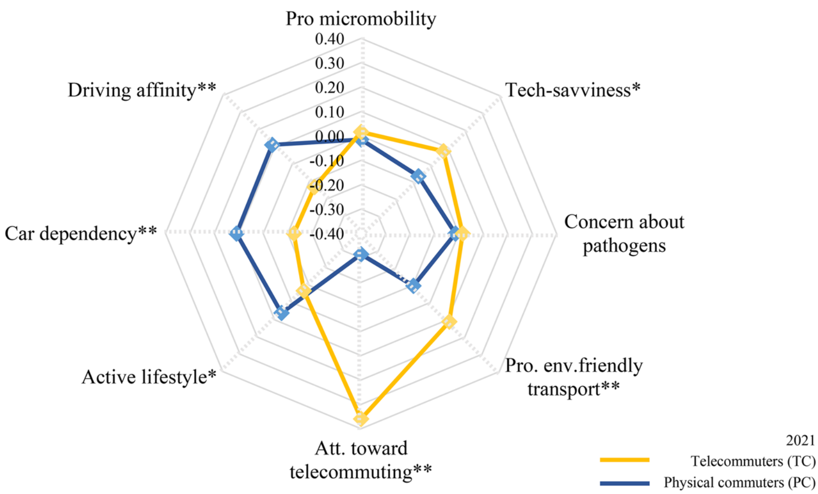


Figure 3. Factor scores (z-standardized) for both groups in the year 2020 (top) and 2021 (bottom). *group difference (TC/PC) significant at 0.05 level; ** at 0.01 level.

(three items), and "tech-savviness" (three items). Additionally, one binary variable was "commute status" in 2020. The two remaining variables were single items: "number of days per week the job allows telecommuting" and "number of days per week a person intends to telecommute in the future" (Appendix B). Detailed statistics, correlations, and reliability for these constructs are detailed in Appendix G.

The confirmatory factor analysis produced adequate goodness of fit statistics for the 2020 data ($\chi^2(61) = 287.11$; $p < .01$; $\chi^2/df = 4.71$; NFI = .878; TLI = 0.873; CFI = .901; RMSEA = 0.064) as well as for the 2021 data ($\chi^2(61) = 316.87$; $p < .01$; $\chi^2/df = 5.20$; NFI = .895; TLI = .889; CFI = .913; RMSEA = .068).

3.4.2. Test of structural model

A good fit of the measurement model was recognized as the basis to test the structural model. Using structural equation modeling, a good model fit was obtained for the 2020 model (χ^2 (67) = 278.81, $p < 0.01$; χ^2/df = 4.04, NFI = .902; TLI = .897; CFI = .924; RMSEA = .058, R^2 = .39) (Table 5), as well as for the 2021 model (χ^2 (67) = 302.28, $p < 0.01$; χ^2/df = 4.512, NFI = .914; TLI = .907; CFI = .932; RMSEA = .062; R^2 = .46) (Table 6). Both models are visualized in Figures 4 and 5, respectively.

4. Discussion

This study contributes to the growing research on COVID-19's impact on transportation, focusing on attitudes and other psychological factors. Using individual-level survey data from California, we examined two groups: those who shifted to telecommuting during the pandemic and those who continued commuting. By examining these groups in 2020 and 2021, we aimed to (I) identify differences in mobility-related attitudes at different pandemic stages, and (II) predict future telecommuting levels using psychological and external factors.

Table 5. Standardized and unstandardized beta-coefficients, and significance levels for the 2020 structural model.

Parameter estimated	Unstandardized (error)	Standardized	p
Concern about path. → Toward tc	.096 (.052)	.083	**
Concern about path. → Group	.030 (.018)	.054	.098
Job allows tc → Toward tc	.192 (.019)	.387	**
Job allows tc → Group	.122 (.007)	.503	**
Toward tc → Group	.106 (.017)	.218	**
Tech-savviness → Toward tc	.122 (.063)	.089	.055
Job allows t → Future intention tc	.356 (.032)	.376	**
Toward tc → Future intention tc	.583 (.075)	.306	**
Group → Future intention tc	.260 (.137)	.066	.057
Tech-savviness → Future intent.tc	.367 (.092)	.141	**

Table 6. Standardized and unstandardized beta-coefficients, and significance levels for the 2021 structural model.

Parameter estimated	Unstandardized (error)	Standardized	*p*
Concern pathogens → Toward tc	.159 (.021)	.102	**
Concern pathogens → Group	−.007 (.020)	−.011	.707
Job allows tc → Toward tc	.311 (.021)	.546	**
Job allows tc → Group	.110 (.008)	.454	**
Toward tc → Group	.105 (.017)	.247	**
Tech-savviness → Toward tc	.141 (.061)	.092	*
Job allows t → Future intent. tc	.244 (.035)	.257	**
Toward tc → Future intention tc	.797 (.075)	.477	**
Group → Future intention tc	.121 (.134)	.031	.366
Tech-savviness → Future intent. tc	.275 (.081)	.107	**

*Significant at 0.05 level.
**Significant at 0.01 level.

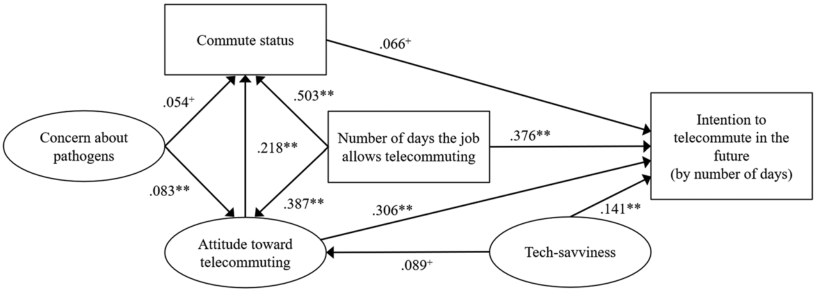


Figure 4. Standardized beta-coefficients, and significance levels within the 2020 structural model. +significant at.10 level, * significant at 0.05 level, ** significant at 0.01 level.

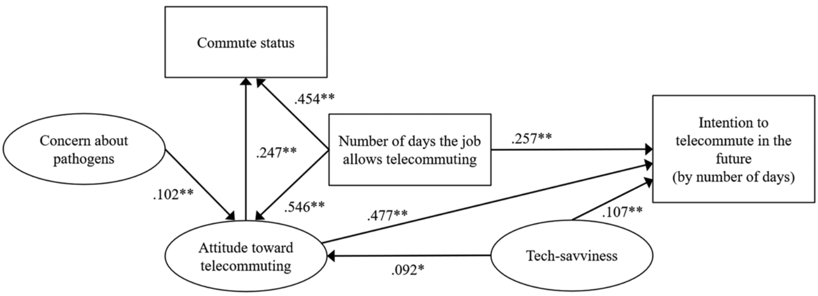


Figure 5. Standardized beta-coefficients, and significance levels within the 2021 structural model. Note: +significant at.10 level, * significant at 0.05 level, ** significant at 0.01 level.

Overall, the study explores how the pandemic's disruption of commuting behavior influences mobility attitudes and future commuting plans.

4.1. Socio-economic findings

The initial socio-economic differences between telecommuters and physical commuters align with previous research (Abreu e Silva et al., 2018; Budnitz et al., 2020; López Soler et al., 2021; Su et al., 2021; Yasenov, 2020). Telecommuters had higher income and education levels, reflecting their roles in desk jobs and managerial positions that allow remote work. Physical commuters' jobs require on-site presence more often and reported fewer telecommuting days (1.75 days compared to 3.52 days for telecommuters).

Notably, no gender, age, or household size (total number of people) differences were found between the groups. For gender, literature has found either very little or no difference (López Soler et al., 2021; Su et al., 2021). The similarity between groups in age may indicate that the decision to telecommute is less influenced by the worker's life stage and more by job-related factors, such as the nature of work or workplace policies. It also suggests that telecommuting opportunities after the COVID-19 pandemic are no longer skewed toward younger, tech-savvy workers or older, established professionals as was the case pre-pandemic (Su et al., 2021). The comparable household sizes across the groups imply that family structure does not strongly differentiate telecommuters from physical commuters. However, there is a slight difference that approaches significance with regard to number of children in the household ($p = 0.15$), which was slightly higher for physical commuters. Parents with more children may face challenges in creating a conducive environment for remote work, leading them to prefer or require on-site roles. Additional data collection would be necessary to fully clarify this finding, but it hints at a potential interaction between family dynamics and job flexibility.

These results highlight how socio-economic factors influence the ability and willingness to telecommute and emphasize the importance of understanding demographics in transportation research, as these disparities certainly also contribute to the identified psychographic differences.

4.2. Psychographic differences

An intriguing finding of our study is the resilience of certain mobility-related psychological factors despite the pandemic's disruption of commuting habits. Attitudes like car dependency, driving affinity, and support for environmentally friendly modes remained stable, indicating these attitudes may be deeply ingrained and resistant to change, potentially reflecting underlying personality traits (Hirsh, 2010).

Car dependency is a multifaceted construct, involving geography, transportation options, and subjective perceptions of alternative modes (Saeidizand et al., 2022), while driving affinity relates to one's affective and symbolic relationship with cars (Steg, 2005). Physical commuters consistently showed higher car dependency and driving affinity, while telecommuters maintained a more positive attitude toward environmentally friendly transport. This suggests that car-reliant individuals are less likely to view alternative modes in a positive light, and may even view them as a threat to car privileges (e.g. the right of way, space, or funding).

These findings highlight the challenges in promoting modal shifts away from car-centric transportation (Hauslbauer, 2023) due to persistent, entrenched attitudes, making it crucial to understand psychological barriers for effective interventions and policies promoting sustainable transport.

Other mobility-related attitudes showed greater variability, influenced by pandemic experiences and exposure to different commuting styles, highlighting the dynamic nature of some psychological factors that are susceptible to external influences.

Concern about pathogens, initially higher among telecommuters, decreased to the same level as physical commuters by 2021, likely due to quarantine fatigue

(Zhao et al., 2020) and vaccine availability, challenging previous claims of long-term pathogen risk effects on mobility. In 2020, tech-savviness was similar between groups, but by 2021, it has become significantly higher among telecommuters. This likely resulted from increased use of technology, leading to greater familiarity and proficiency among telecommuters. Telecommuters also reported a more active lifestyle, as expected, possibly due to saved time and reduced stress, giving individuals more time to engage in physical activity (de Haas et al., 2020).

These findings underscore the need for transportation research to consider both stable and evolving psychological factors when studying travel behavior and promoting sustainable mobility, and recognizing which factors may not be readily changed by interventions.

4.3. Intentions to telecommute in the future

The 2020 dataset showed a good statistical fit for the model, but the 2021 model revealed a decline in the significance of "concern about pathogens" and "group status". The predictive power of concern about pathogens decreased from 2020 to 2021, likely due to quarantine fatigue (Zhao et al., 2020), though it still indirectly influenced the intention to telecommute through attitudes toward telecommuting. "Group status" lost its predictive power in 2021, suggesting that factors like vaccination rates and remote-work policies have rendered initial telecommuting experiences less influential in shaping telecommuting intentions over time.

Instead, workplace policy—specifically, how much a job allows telecommuting—emerged as a crucial predictor of teleworking intentions, reflecting perceived behavioral control in the theory of planned behavior (Ajzen, 1991). This indicates that job flexibility significantly influences telecommuting ability and intentions. This underscores the importance of structural factors, such as job flexibility, in shaping individual intentions towards telecommuting. Attitude toward telecommuting, another core aspect of the theory of planned behavior (Ajzen, 1991), emerged as the strongest predictor of future telecommuting intentions, surpassing job flexibility. This supports Mokhtarian and Salomon's (Mokhtarian & Salomon, 1997) view that while job flexibility is necessary, it alone is not sufficient for telecommuting adoption. Therefore, if an increase in telecommuting is the goal, policy interventions should focus on addressing both structural and individual factors.

On a structural level, enhancing job flexibility through corporate and government policies can facilitate telecommuting adoption, particularly in industries conducive to remote work, like IT, administration, consulting, or insurance (Destatis \(Statistisches Bundesamt\), 2022). On an individual level, while attitudes toward telecommuting are harder to change, our model suggests that improving tech-savviness can positively influence beliefs about the benefits of telecommuting, thereby promoting its adoption.

Finally, we want to draw attention to the emergence of hybrid work. Research (Wigert & Agrawal, 2022) has shown a shift towards hybrid work, with hybrid arrangements surpassing exclusive remote work among US remote-capable employees in 2022. Our study found that telecommuters, initially working from home full-time, plan to telework an average of 3.57 days per week in the future. This suggests that remote-capable individuals are considering *how much* telework to incorporate rather than *whether* to do it. Current research on hybrid work is needed to optimize both productivity and well-being (Hopkins & Bardoel, 2023). For transportation research and policy, understanding hybrid workers' travel behavior is crucial (Moglia et al., 2021). While our study deepens understanding of telework frequency determinants, further research is necessary on hybrid workers' travel behavior, including their needs, preferences, and the impact on transportation networks. With reduced daily commuting, promoting flexible mobility solutions and shared modes of transportation can prioritize sustainability

4.4. Implications for quality of life

Building on these findings, we see clear implications for improving livability through promoting hybrid work arrangements. Telecommuting can improve work-life balance by reducing stress and frustration associated with daily commuting (Chatterjee et al., 2020) and offering greater control over one's schedule. This flexibility enables individuals to dedicate more time to an active lifestyle, as shown in the present study, as well as to personal pursuits or family, all of which are vital to improving well-being (Ryff & Keyes, 1995). Reduced reliance on commuting, particularly during peak hours, also helps mitigating road congestion and lower greenhouse gas emissions (Kissinger & Reznik, 2019), contributing to more sustainable environments. Furthermore, the shift towards hybrid work, indicated by our findings, offers the opportunity to reclaim urban space from parked cars, fostering greener, more pedestrian-friendly cities.

Promoting telecommuting beyond the pandemic can not only support individual well-being for those who are able to work from home, but may also foster greener, less car-dependent cities, creating improvements in livability for everyone.

4.5. Limitations

First, this study uses a quasi-experimental design. This is particularly relevant when considering the impact of socio-economic status. We controlled for this by including income and education in the prediction model, and found that they did not significantly affect telecommuting intentions, and the predictive value of remaining variables remained largely unchanged. However, this limitation should be considered when interpreting attitudinal differences.

Second, some variables in the model are barely ordinal and required specific recoding decisions. For example, job telecommuting allowance was coded on a scale from 0 to 5 (from 0 "never" to 5 "5 or more times a week"), which does not directly reflect the number of telecommuting days per week. Additionally, the "flex/variable schedule" option in the dependent variable was imputed with the sample mean, though different interpretations by participants could have influenced results. Imputing this variable with 0 showed that our original mean yielded better R^2 results, supporting our method, but alternative coding decisions could have affected findings.

Lastly, the item "I like riding my bike" required careful consideration. In the factor analysis, it fell just short of our predetermined cutoff of 0.5 in 2020 (0.445), but performed well in 2021 (0.663). Despite this, we decided to retain it in the MANOVA analysis, as it was close to the threshold and contributed valuable information to the pro-micro mobility construct overall. Additionally, the composition of the active lifestyle construct varied between 2020 and 2021, making direct comparison challenging. To address this, we used the simple mean of two consistent items (excluding "I like riding my bike"), which confirmed our hypothesis. However, including other items might have yielded different results, indicating the need for further research on the active lifestyle construct.

4.6. Implications for future research

Our study reveals several intriguing avenues for future research. First, using a dataset with more measurement points over a longer period could enhance the theoretical understanding of the co-evolution between attitudes and behavioral intentions, potentially using latent transition analysis (Kroesen et al., 2017). Another promising direction is collecting post-pandemic data on various commuter types. Insights into how telecommuting frequency and days influence hybrid workers' attitudes and mobility behaviors could be valuable. Additionally, examining the experiences of individuals transitioning from telecommuting to full on-site work could provide further understanding. Given the current stabilization of the post-pandemic landscape, opportunities for data collection to address these topics should soon be available. Finally, investigating the relationship between tech-savviness and telecommuting attitudes, and exploring ways to enhance tech-savviness among workers, could be beneficial.

4.7. Conclusions

This study illuminates the impact of the COVID-19 pandemic on individuals' psychological factors related to mobility, through the forced disruption of habitual commuting behavior.

While it's understood that attitudes and behavior influence each other, our research reveals a nuanced insight: certain attitudes remain resilient to external disruptions, such as car dependency and affinity for driving, while others are highly affected, such as concern about pathogens and tech-savviness. Specifically, the entrenched attitudes pose challenges for efforts aimed at promoting modal shifts away from car-centric transportation. Understanding and considering both stable and evolving psychological factors in future transportation research is crucial for promoting sustainable mobility effectively.

Moreover, we found attitudes to be even more influential than job requirements in predicting telecommuting intentions. Notably, attitude is highly and directly shaped by tech-savviness, which provides a concrete lever to bridge the gap between attitudes and behavior.

While constraints on telecommuting persist, this paper asserts the emergence of telecommuting as a viable societal option, foreseeing hybrid work as the future norm. Beyond potential transportation improvements such as expanded mode choices, additional societal advantages were unveiled: individuals have developed a more positive attitude toward an active lifestyle, and telecommuters have significantly enhanced their tech-savviness.

This study illuminates strategies for leveraging individual and external factors to advance telecommuting, which promises benefits for both individuals and society at large.

Acknowledgements

The data collection for this project was made possible through funding received by the University of California Institute of Transportation Studies from the State of California via the Public Transportation Account and the Road Repair and Accountability Act of 2017 (SB 1), and funding from the California Air Resources Board (CARB). Additional funding was provided by the 3 Revolutions Future Mobility (3RFM) Program of the University of California, Davis. The authors would like to thank the State of California, CARB and the 3RFM program for their support of university-based research in transportation, and especially for the funding provided in support of this project. The authors would like to thank Grant Matson, Keita Makino, Yongsung Lee, Bailey Affolter, Tak Chun Marcus Chan, Mikayla Elder, Sean McElroy, Misch Young, Jaime Soza Parra, Dillon Fitch and other colleagues at the University of California, Davis and other institutions who contributed to the survey design, data collection, and data management.The stay of author A. L. Hauslbauer at the University of California, Davis and the work related to this paper was made possible through funding received by the German Federal Ministry for Foreign Affairs through the German Academic Exchange Service (DAAD). This work was further supported by TUD Dresden University of Technology, and the Boysen-TU Dresden-Research Training Group. The authors would like to thank Julia Lopez and Sajjad Haider for their support and feedback.The AI chatbot ChatGPT by OpenAI was used to correct spelling and grammar, and to find synonymous expressions where necessary.

Authors' contributions

Dr. Andrea Lucia Hauslbauer, Conceptualization, Methodology, Formal analysis, Investigation, Writing – Original draft, Writing – Review and editing, Visualization. Dr. Jai Malik,

Conceptualization, Methodology, Formal analysis, Investigation, Resources, Data Curation, Writing – Review and editing. Dr. Xiatian Iogansen, Conceptualization, Methodology, Formal analysis, Investigation, Resources, Data Curation, Writing – Review and editing. Prof. Dr. Giovanni Circella, Conceptualization, Methodology, Investigation, Resources, Data Curation, Writing – Review and editing, Supervision, Funding acquisition. Prof. Dr. Tibor Petzoldt, Conceptualization, Methodology, Writing - Review & Editing, Supervision.

Disclosure statement

No potential conflict of interest was reported by the author(s).

ORCID

Andrea L. Hauslbauer http://orcid.org/0000-0002-1673-7475
Jai Malik http://orcid.org/0000-0002-7137-7302
Giovanni Circella http://orcid.org/0000-0003-1832-396X
Xiatian Iogansen http://orcid.org/0000-0002-4851-1323
Tibor Petzoldt http://orcid.org/0000-0003-3162-9656

References

Aarts, H., & Dijksterhuis, A. (2000). The automatic activation of goal-directed behaviour: The case of travel habit. *Journal of Environmental Psychology*, *20*(1), 75–82. https://doi.org/10.1006/jevp.1999.0156

Abreu e Silva, J. de, & Melo, P. C. (2018). Does home-based telework reduce household total travel? A path analysis using single and two worker British households. *Journal of Transport Geography*, *73*, 148–162. https://doi.org/10.1016/j.jtrangeo.2018.10.009

Ahmed, A., & Stopher, P. (2014). Seventy minutes plus or minus 10—A review of travel time budget studies. *Transport Reviews*, *34*(5), 607–625. https://doi.org/10.1080/01441647.2014.946460

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, *50*(2), 179–211. https://doi.org/10.1016/0749-5978(91)90020-T

Anke, J., Francke, A., Schaefer, L. -M., & Petzoldt, T. (2021). Impact of SARS-CoV-2 on the mobility behaviour in Germany. *European Transport Research Review*, *13*(1), 10. https://doi.org/10.1186/s12544-021-00469-3

Backhaus, K., Erichson, B., Plinke, W., & Weiber, R. (2016). *Multivariate Analysemethoden*. Springer.

Bartz, F. M. (2015). *Mobilitätsbedürfnisse und ihre Satisfaktoren. Die Analyse von Mobilitätstypen im Rahmen eines internationalen Segmentierungsmodells* [Doctoral dissertation].

Bergkvist, L., & Rossiter, J. R. (2007). The predictive validity of multiple-item versus single-item measures of the same constructs. *Journal of Marketing Research*, *44*(2), 175–184. https://doi.org/10.1509/jmkr.44.2.175

Borkowski, P., Jażdżewska-Gutta, M., & Szmelter-Jarosz, A. (2021). Lockdowned: Everyday mobility changes in response to COVID-19. *Journal of Transport Geography*, *90*, 102906. https://doi.org/10.1016/j.jtrangeo.2020.102906

Brette, O., Buhler, T., Lazaric, N., & Marechal, K. (2014). Reconsidering the nature and effects of habits in urban transportation behavior. *Journal of Institutional Economics*, *10*(3), 399–426. https://doi.org/10.1017/S1744137414000149

Budnitz, H., Tranos, E., & Chapman, L. (2020). Telecommuting and other trips: An English case study. *Journal of Transport Geography*, *85*, 102713. https://doi.org/10.1016/j.jtrangeo.2020.102713

Burd, C., Burrows, M., & Brian, M. (2021). *Travel time to work in the United States: 2019: American Community survey reports*. census.gov/content/dam/census/library/publications/2021/acs/acs-47.pdf

Burghard, U., & Dütschke, E. (2019). Who wants shared mobility? Lessons from early adopters and mainstream drivers on electric carsharing in Germany. *Transportation Research Part D: Transport and Environment*, *71*, 96–109. https://doi.org/10.1016/j.trd.2018.11.011

Chai, L., Xu, J., & Li, S. (2023). Investigating the intention to adopt telecommuting during COVID-19 outbreak: An integration of TAM and TPB with risk perception. *International Journal of Human–Computer Interaction*, *39*(18), 3516–3526. https://doi.org/10.1080/10447318.2022.2098906

Chatterjee, K., Chng, S., Clark, B., Davis, A., De Vos, J., Ettema, D., Handy, S., Martin, A., & Reardon, L. (2020). Commuting and wellbeing: A critical overview of the literature with implications for policy and future research. *Transport Reviews*, *40*(1), 5–34. https://doi.org/10.1080/01441647.2019.1649317

Circella, G., Iogansen, X., Makino, K., Compostella, J., Young, M., & Malik, J. K. 2023. Investigating the temporary and longer-term impacts of the COVID-19 pandemic on mobility in California. https://doi.org/10.7922/G23X84ZS

Circella, G., Matson, G., Alemi, F., & Handy, S. (2019). *Panel study of emerging transportation technologies and trends in California: Phase 2 data collection*. https://escholarship.org/content/qt35x894mg/qt35x894mg.pdf

Copenhagenize Design Co. (2024). Retrieved March 9, 2024, from https://copenhagenize.eu/

Costello, A. B., & Osborne, J. (2009). Best practices in exploratory factor analysis: Four recommendations for getting the most from your analysis. *Pan-Pacific Management Review*, *12*(2), 7.

de Haas, M., Faber, R., & Hamersma, M. (2020). How COVID-19 and the Dutch 'intelligent lockdown' change activities, work and travel behaviour: Evidence from longitudinal data in the Netherlands. *Transportation Research Interdisciplinary Perspectives*, *6*, 100150. https://doi.org/10.1016/j.trip.2020.100150

Destatis (Statistisches Bundesamt). (2022). *Ein Viertel aller Erwerbstätigen arbeitete 2021 im homeoffice*. Retrieved March 8, 2024, from https://www.destatis.de/DE/Presse/Pressemitteilungen/Zahl-der-Woche/2022/PD22_24_p002.html#:~:text=In%20der%20Verwaltung%20und%20F%C3%BChrung,Besch%C3%A4ftigten%20(66%2C2%20%25)

Drolet, A. L., & Morrison, D. G. (2001). Do we really need multiple-item measures in service research? *Journal of Service Research*, *3*(3), 196–204. https://doi.org/10.1177/109467050133001

Engle, S., Stromme, J., & Zhou, A. (2020). *Staying at home: Mobility effects of COVID-19*. https://doi.org/10.2139/ssrn.3565703

Festinger, L. (1962). *A theory of cognitive dissonance*. Stanford University Press.

Field, A. (2013). *Discovering statistics using IBM SPSS Statistics*. Sage Publications Ltd.

Gardner, B. (2015). A review and analysis of the use of 'habit' in understanding, predicting and influencing health-related behaviour. *Health Psychology Review*, *9*(3), 277–295. https://doi.org/10.1080/17437199.2013.876238

Hair, F., Black, W., Babin, B., & Anderson, R. (2010). *Multivariate data analysis* (7th ed.). Prentice Hall.

Hauslbauer, A. L. (2023). *Pathways toward the reduction of private car use from a psychological perspective* [Doctoral dissertation]. Dresden University of Technology. Qucosa. https://nbn-resolving.org/urn:nbn:de:bsz:14-qucosa2-891760

Hauslbauer, A. L., Schade, J., Drexler, C. E., & Petzoldt, T. (2022). Extending the theory of planned behavior to predict and nudge toward the subscription to a public transport ticket. *European Transport Research Review*, *14*(1), 5. https://doi.org/10.1186/s12544-022-00528-3

Hirsh, J. B. (2010). Personality and environmental concern. *Journal of Environmental Psychology*, *30*(2), 245–248. https://doi.org/10.1016/j.jenvp.2010.01.004

Hopkins, J., & Bardoel, A. (2023). The future is hybrid: How organisations are designing and supporting sustainable hybrid work models in post-pandemic Australia. *Sustainability*, *15*(4), 3086. https://doi.org/10.3390/su15043086

Iogansen, X., Compostella, J., Makino, K., & Circella, G. (2022). A longitudinal analysis of the heterogeneous changes in travel behaviors in response to the COVID-19 pandemic in the United States. Presented at *TRB, TRB 101 Annual Meeting*, Poster presentation session 1221.

Kissinger, M., & Reznik, A. (2019). Detailed urban analysis of commute-related GHG emissions to guide urban mitigation measures. *Environmental Impact Assessment Review*, *76*, 26–35. https://doi.org/10.1016/j.eiar.2019.01.003

Kroesen, M., Handy, S., & Chorus, C. (2017). Do attitudes cause behavior or vice versa? An alternative conceptualization of the attitude-behavior relationship in travel behavior modeling. *Transportation Research Part A: Policy and Practice*, *101*, 190–202. https://doi.org/10.1016/j.tra.2017.05.013

López Soler, J., Christidis, P., & Vassallo, J. (2021). Teleworking and online shopping: Socio-economic factors affecting their impact on transport demand. *Sustainability*, *13*(13), 7211. https://doi.org/10.3390/su13137211

Marsden, G., Anable, J., Chatterton, T., Docherty, I., Faulconbridge, J., Murray, L., Roby, H., & Shires, J. (2020). Studying disruptive events: Innovations in behaviour, opportunities for lower carbon transport policy? *Transport Policy*, *94*, 89–101. https://doi.org/10.1016/j.tranpol.2020.04.008

Matson, G., McElroy, S., Yongsung, L., & Circella, G. (2021). *Longitudinal analysis of COVID-19 impacts on mobility: An early snapshot of the emerging changes in travel behavior*. https://escholarship.org/content/qt2pg7k2gt/qt2pg7k2gt.pdf

Moglia, M., Hopkins, J., & Bardoel, A. (2021). Telework, hybrid work and the United Nation's sustainable development goals: Towards policy coherence. *Sustainability*, *13*(16), 9222. https://doi.org/10.3390/su13169222

Mokhtarian, P. L., & Salomon, I. (1997). Modeling the desire to telecommute: The importance of attitudinal factors in behavioral models. *Transportation Research Part A: Policy and Practice*, *31*(1), 35–50. https://doi.org/10.1016/s0965-8564(96)00010-9

Moody, J., & Zhao, J. (2020). Travel behavior as a driver of attitude: Car use and car pride in U.S. cities. *Transportation Research Part F: Traffic Psychology and Behaviour*, *74*, 225–236. https://doi.org/10.1016/j.trf.2020.08.021

Nunnally, J. C. (1967). *Psychometric theory*. McGraw-Hill.

Przybylowski, A., Stelmak, S., & Suchanek, M. (2021). Mobility behaviour in view of the impact of the COVID-19 pandemic—Public transport users in Gdansk Case Study. *Sustainability*, *13*(1), 364. https://doi.org/10.3390/su13010364

Redmond, L. (2000). *Identifying and analyzing travel-related attitudinal, personality, and lifestyle clusters in the San Francisco Bay Area* [Dissertation]. University of California.

Richiardi, L., Pizzi, C., & Pearce, N. (2013). Commentary: Representativeness is usually not necessary and often should be avoided. *International Journal of Epidemiology*, *42*(4), 1018–1022. https://doi.org/10.1093/ije/dyt103

Rose, P. A., & Brown, S. (2021). Reconstructing attitudes towards work from home during COVID-19: A survey of South Korean managers. *Behavioral Sciences*, *11*(12), 163. https://doi.org/10.3390/bs11120163

Ryff, C. D., & Keyes, C. L. M. (1995). The structure of psychological well-being revisited. *Journal of Personality and Social Psychology*, *69*(4), 719–727. https://doi.org/10.1037/0022-3514.69.4.719

Saeidizand, P., Fransen, K., & Boussauw, K. (2022). Revisiting car dependency: A worldwide analysis of car travel in global metropolitan areas. *Cities*, *120*, 103467. https://doi.org/10.1016/j.cities.2021.103467

San Francisco Smart City Challenge. (2016). Retrieved March 9, 2024, from http://smartcitysf.com/

Schendera, C. (2010). *Clusteranalyse mit SPSS* [Cluster analysis with SPSS]. Oldenburg Wissenschaftsverlag GmbH.

Schlag, B., Schade, J., & Risser, R. (2007). Psychologische Grundlagen der Steuerung von Mobilität. In H.-P. Krüger (Hrsg.), *Enzyklopädie der Psychologie: Praxisgebiet 6: Verkehrspsychologie, Bd. 1*. Verkehrsverhalten.

Scorrano, M., & Danielis, R. (2021). Active mobility in an Italian city: Mode choice determinants and attitudes before and during the COVID-19 emergency. *Research in Transportation Economics*, *86*, 101031. https://doi.org/10.1016/j.retrec.2021.101031

Steg, L. (2005). Car use: Lust and must. Instrumental, symbolic and affective motives for car use. *Transportation Research Part A: Policy and Practice*, *39*(2-3), 147–162. https://doi.org/10.1016/j.tra.2004.07.001

Streiner, D. L. (2003). Starting at the beginning: An introduction to coefficient alpha and internal consistency. *Journal of Personality Assessment*, *80*(1), 99–103. https://doi.org/10.1207/S15327752JPA8001_18

Su, R., McBride, E. C., & Goulias, K. G. (2021). Unveiling daily activity pattern differences between telecommuters and commuters using human mobility motifs and sequence analysis. *Transportation Research Part A: Policy and Practice*, *147*, 106–132. https://doi.org/10.1016/j.tra.2021.03.002

UC Davis Mobility Study. (2024). Retrieved March 8, 2024, from https://postCOVID19mobility.sf.ucdavis.edu

Wanous, J. P., Reichers, A. E., & Hudy, M. J. (1997). Overall job satisfaction: How good are single-item measures? *The Journal of Applied Psychology*, *82*(2), 247–252. https://doi.org/10.1037/0021-9010.82.2.247

Warren, M. S., & Skillman, S. W. (2020). *Mobility changes in response to COVID-19*. arXiv. https://doi.org/10.48550/arXiv.2003.14228

Wigert, B., & Agrawal, S. (2022). *Returning to the office: The current, preferred and future state of remote work*. Retrieved June 19, 2023, from https://www.gallup.com/workplace/397751/retur ning-office-current-preferred-future-state-remote-work.aspx

Worthington, R. L., & Whittaker, T. A. (2006). Scale development research: A content analysis and recommendations for best practices. *The Counseling Psychologist*, *34*(6), 806–838. https://doi.org/10.1177/0011000006288127

Yasenov, V. (2020). Who can work from home? *SSRN Electronic Journal*. IZA Discussion Paper No. 13197. https://doi.org/10.2139/ssrn.3590895

Zarabi, Z., Manaugh, K., & Lord, S. (2019). The impacts of residential relocation on commute habits: A qualitative perspective on households' mobility behaviors and strategies. *Travel Behaviour and Society*, *16*, 131–142. https://doi.org/10.1016/j.tbs.2019.05.003

Zhao, J., Lee, M., Ghader, S., Younes, H., Darzi, A., Xiong, C., & Zhang, L. (2020). *Quarantine fatigue: First-ever decrease in social distancing measures after the COVID-19 outbreak before reopening United States*. https://arxiv.org/pdf/2006.03716

Appendix A

Table A1. Six groups of individuals in fall 2020 survey among respondents from State of California, frequency (N) and Percentage (%).

	Six groups of individuals	N	%
1	Those who had ever commuted for school/ work at both time points	1,343	34%
1-a	Those who both phys. commuted and studied/ worked remotely at both timepoints	194	5%
1-b	Those who used hybrid mode in fall 2019, but commuted entirely fall 2020	12	0.3%
1-c	Those who commuted entirely in 2019, but used hybrid mode in fall 2020	525	13%
1-d	Those who commute entirely in both time points	613	15%
2	Those who started remote study/work entirely during the pandemic	854	21%
3	Those who studied/worked remotely entirely at both timepoints	91	2%

Among Group 1 and Group 2, 981 of participants also participated in the fall 2021 survey and provided high-quality responses, thus constituting the final sample for this study at Group 1 with 523 participants and Group 2 with 458 participants.

Appendix B

Table B1. Additional items used for the model from the 2021 questionnaire and respective scales.

Household income (annual, in US$)									
Coding:	1 = <25.000, 2 = 25.000-49.999, 3 = 50.000-74.999, 4 = 75.000-99.999, 5 = 100.000-149.999, 6 = 150.000-199.999, 7 = > 200.000								
	Assume there was no pandemic. Please answer the follow-ing questions regarding the possibility of teleworking at your job.								
Job allows telework	What is the maximum frequency that the nature of your job would allow you to telework?								
Scale:	never	less than once a month	1-3 times a month	1-2 times a week	3-4 times a week	5 or more times a week			
	0	1	2	3	4	5			
Future telework	*What day(s) of the week would you like to telework once the pandemic is over?*								
Scale:	Mon-day	Tues-day	Wed-nesday	Thurs-day	Friday	Satur-day	Sund-ay	Flex/ variable sched.	Will not/ don't want to telework
	1	2	3	4	5	6	7	8	0
Coding:	Number of days with teleworking intention, if "Flex/variable schedule": imputed mean of days with teleworking intention (2.08 for the reduced sample, $N = 909$)								
	Commute status (binary variable; Iogansen et al., 2022)								
1, PC	Commuted for both timepoints								
2, TC	Started remote study/work entirely during the pandemic								

Appendix C

Qualitative analysis of 72 participants

Among the telecommuter group, 72 individuals reported telecommuting despite job constraints. Analysis of open-ended survey responses on the pandemic's impact on income and employment revealed that 66% of respondents worked reduced hours, resulting in decreased income. Their answers suggest that telecommuting may not be effective, often due to job nature or home circumstances (e.g., remote but "not efficient", "classes cancelled", "did not work well due to mentally challenged adult son at home"). 32% of respondents work in education, significantly more than the overall sample (12.5%), and 13% cited various forms of unemployment. 21% had diverse responses, such as increased work hours or working fully on-site without explanation for selecting telecommuting.

In conclusion, although the majority of the 72 special cases engage at least partly in telecommuting, their circumstances led them to indicate that their jobs do not really allow this. Recognizing the potential bias in analyzing these cases at group level, we took the extra step of data cleaning, excluding them from our model. This ensures a clear distinction between physical commuters and those who exclusively telecommute.

Appendix D

Constructs consisting of two items only

Three of the eight constructs consisted of two items only. Two-item constructs run the risk of being unstable (Costello & Osborne, 2009), especially if they are conceptualized as multidimensional. But if a construct is narrowly defined, assessing it with as little as one item may be acceptable (Bergkvist & Rossiter, 2007; Drolet & Morrison, 2001; Wanous et al., 1997). In fact, a two-item construct can be considered reliable when the items correlate highly but remain relatively uncorrelated with other items (Worthington & Whittaker, 2006, p. 821). To assess whether the three two-item constructs in the present analysis can be considered stable, the respective items were correlated with all remaining items. For the construct car dependency, the two items correlate acceptably with each other ($r = .51$), and little with all other items ($r < .30$). For the construct active lifestyle, the two items correlate acceptably with each other ($r = .51$), and little with all other items ($r < .32$). For the construct driving affinity, the two items correlate acceptably with each other ($r = .62$), and little with all other items ($r < .39$). We conclude that, while the assessment of these items may not be perfect using only two items, judging from these correlations and the construct reliability (Table 3), we can proceed with these items and judge them as stable.

Appendix E

Table E1. MANOVA results of attitudinal group differences (PC and TC) for 2020 and 2021.

	2020		2021	
Construct	F (df1, df2)	*p*	F (df1, df2)	*p*
Pro micromob.	F(1, 979) = .001	> .05.	F(1, 979) = .230	> .05.
Att. toward tc	F(1, 979) = 89.44	**	F(1, 979) = 125.254	**
Driving affinity	F(1, 979) = 12.20	**	F(1, 979) = 14.800	**
Concern ab. path.	F(1, 979) = 6.21	*	F(1, 979) = .217	> .05
Active lifestyle	F(1, 979) = 0.588	> .05	F(1, 979) = 4.075	*
Tech-savviness	F(1, 979) = 0.620	> .05	F(1, 979) = 5.143	*
Pro.env.transport	F(1, 979) = 15.480	**	F(1, 979) = 10.626	**
Car dependency	F(1, 979) = 26.099	**	F(1, 979) = 13.653	**

***Significant at .01 level.
*Significant at .05 level.

Appendix F

Table F1. Means and respective standard deviations of constructs (scale 1-5) for both years and groups.

		Group 1 PC (N = 523)		Group 2 TC (N = 458)		Total (N = 981)	
	Year	Mean	SD	Mean	SD	Mean	SD
Pro micro-mobility	2020	2.68	0.95	2.68	0.91	2.68	0.93
	2021	2.69	0.98	2.72	0.92	2.71	0.95
Driving affinity	2020	3.84	1.05	3.53	1.16	3.70	1.12
	2021	3.77	1.08	3.47	1.18	3.63	1.14
Concern ab. path.	2020	3.63	1.03	3.79	0.92	3.71	0.98
	2021	3.15	1.13	3.20	1.11	3.17	1.12
Tech-savviness	2020	3.48	0.86	3.46	0.83	3.47	0.85
	2021	3.51	0.90	3.41	0.85	3.47	0.88
Pro env. friendly transport	2020	2.96	1.09	3.22	1.05	3.08	1.08
	2021	3.00	1.01	3.22	1.00	3.1	1.01
Active lifestyle	2020	4.23	0.83	4.28	0.71	4.25	0.78
	2021	4.22	0.81	4.32	0.71	4.26	0.77
Car dependency	2020	3.37	1.17	3.01	1.22	3.2	1.21
	2021	3.45	1.18	3.15	1.19	3.31	1.19
Attitude toward telecommuting	2020	2.79	0.76	3.28	0.85	3.02	0.84
	2021	2.81	0.89	3.44	0.87	3.10	0.92

Appendix G

Overview and descriptive statistics for items and constructs, correlations among constructs, scale reliability, and validity

Table G1. Simple means, standard deviations, and scales for the constructs, N = 909.

Variable	M	SD	Scale/Code
Att. toward telecommuting 2020	3.01	.83	Strongly disagree (1)
Att. toward telecommuting 2021	3.10	.91	– Strongly agree (5)
Concern about pathogens 2020	3.70	.98	
Concern about pathogens 2021	3.17	1.11	
Tech-savviness 2020	3.48	.86	
Tech-savviness 2021	3.47	.89	
Max. frequency of job allowing telework	2.78	2.04	0 – 5 or more days
# of days of intended future telework	2.51	1.94	0 – 7 days[2]
Group (physical commuters)	57.5%		

Table G2. Pearson correlations of constructs of Table 13, N = 909.

	Att. tc 20	Att tc 21	Con. p. 20	Con. p. 21	Tech 20	Tech 21	Job all. tc
Att. toward tc 2020	1						
Att. toward tc 2020	.66**	1					
Concern ab. pathogens 2020	.07	.08*	1				
Concern ab. pathogens 2021	.08*	.09**	.47**	1			
Tech-savviness 2020	−.02	.02	.06	.11*	1		
Tech-savviness 2021	−.03	.02	.03	.08*	.751**	1	
Max. frequ. job all. telecom.	.28**	.40**	.04	.02	.09**	.06	1
Group (1 = PC, 2 = TC)	.31**	.37**	.08*	.02	.00	−.05	.59**

*Significant at 0.05 level.
**Significant at 0.01 level (2-sided).

Table G3. Scale reliability, N = 909.

Construct	Item	Corrected Item-total correlation	Cronbach's α
Attitude toward telecommuting 2020	ATC1	.503	.739
	ATC3	.554	
	ATC5	.474	
	ATC8	.422	
	ATC9	.563	
Attitude toward telecommuting 2021	ATC1	.544	.766
	ATC3	.539	
	ATC5	.530	
	ATC8	.503	
	ATC9	.559	
Concern about pathogens 2020	AT24	.460	.669
	AT27	.506	
	AT28	.477	
Concern about pathogens 2021	AT24	.664	.766
	AT27	.510	
	AT28	.634	
Tech-savviness 2020	AT14	.456	.613
	AT16	.367	
	AT18	.451	
Tech-savviness 2021	AT14	.532	.645
	AT16	.367	
	AT18	.479	

Normality assumption and construct validity

The data met the normality assumption, as evidenced by the skewness and kurtosis values within +/−2 and +/−4, respectively (Field, 2013). To assess construct validity, both convergent and discriminant validity were examined (Hair et al., 2010). While standardized loading estimates > .70, average variance extracted (AVE) >.50 and composite reliability >.70 were not consistently achieved for convergent validity (Table G4), the results were still deemed acceptable for the analysis to proceed as discriminant validity was consistently satisfactory (AVE estimates exceeding the square of the correlation between factors, Table G5).

Table G4. Convergent validity, N = 909.

Variable	Item	lambda	AVE	Composite reliability
Attitude toward telecommuting 2020	ATC1	.592	.365	.739
	ATC3	.630		
	ATC8	.477		
	ATC9	.720		
	ATC5	.578		
Attitude toward telecommuting 2021	ATC1	.607	.279	.787
	ATC3	.574		
	ATC5	.635		
	ATC8	.541		
	ATC9	.745		
Concern about pathogens 2020	AT24	.597	.405	.671
	AT27	.689		
	AT28	.620		
Concern about pathogens 2021	AT24	.837	.540	.775
	AT27	.575		
	AT28	.767		
Tech-savviness 2020	AT14	.652	.359	
	AT16	.477		.783
	AT18	.652		
Tech-savviness 2021	AT14	.786		
	AT16	.448	.402	.658
	AT18	.623		

Table G5. Discriminant validity, N = 909.

	Att. tc 2020	Att. tc 2021	Path c. 2020	Path c. 2021	Tech-s. 2020	Tech-s. 2021
Att. toward tc 2020	**.365**					
Att. toward tc 2021	/	**.279**				
Concern about path. 2020	.005	/	**.405**			
Concern about path. 2021	/	.008	/	**.540**		
Tech-savviness 2020	.000	/	.004	/	**.359**	
Tech-savviness 2021	/	.000	/	.006	/	**.402**
# days job allows tc	.078	.160	.002	.000	.008	.004
Group (1 = PC, 2 = TC)	.096	.137	.006	.000	.000	.003

/ excluded because the different years are not in model together.