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Unveiling substitution patterns of work trips by teleworking and their associations with physical and virtual accessibility in the Brazilian COVID-19 crisis

Jorge Ubirajara Pedreira Junior *, Cira Souza Pitombo

Department of Transportation Engineering, São Carlos School of Engineering, University of São Paulo, São Carlos, Brazil

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ABSTRACT

This research investigates substitution patterns of work trips by teleworking during the COVID-19 pandemic in Brazil. Through a longitudinal survey, individuals were asked about their frequencies of work trips and teleworking, engagement with Information and Communication Technologies (ICT) and physical accessibility aspects. Using a two-step modeling framework, we revealed three different substitution patterns of work trips by teleworking by comparing the 2nd half of 2020 to the pre-pandemic period (early March 2020): (1) no/low - substitution (uninterrupted in-person work), (2) moderate substitution and (3) intense substitution. Moderate substitution was distinguished from intense substitution by the way in-person work was replaced (partially or fully working from home, respectively) and by the proportion of tasks amenable to telework in the individuals' occupations. After controlling for these aspects, positive attitudes towards ICT and ICT proficiency strongly determined the magnitude of substitution. Interestingly, the level of substitution was also positively correlated with physical accessibility, indicating that the pandemic has likely widened existing inequalities. In the follow-up survey in late 2021, we found that no/low substitution and moderate substitution classes returned to pre-pandemic levels of teleworking, whereas most of those in the intense substitution group carried on teleworking in 2021. Car use for the no/low and moderate substitution classes persisted throughout time and only a partial recovery in public transit use was observed in the intense substitution class. In addition to contributing to the comprehension of this phenomenon, the present study provides relevant inputs to inform post-pandemic urban policies.

1. Introduction

The COVID-19 pandemic has severely affected the organization of human activities and, inevitably, urban mobility patterns (Benita, 2021; Paul et al., 2022; Sharifi and Khavarian-Garmsir, 2020). Either enforced by coercive non-pharmacological measures or by voluntarily precautionary behavior, the frequency of in-person activities dropped substantially worldwide (Barbieri et al., 2020). Nevertheless, with the assistance of Information and Communication Technologies (ICT), some of these activities were replaced by their virtual counterparts, such as teleworking, e-learning and online shopping (Mamani-Benito et al., 2022). Considering the potential of new or unfamiliar events to modify long-term habits (Gardner, 2009), the question of how these temporary effects will impact future travel behavior still remains to be answered (Echegaray, 2021). Moreover, it is of great importance to understand under which circumstances specific behaviors were more likely to emerge and persist.

Despite the uniqueness of the COVID-19 crisis, the interplay between ICT and activity-travel behavior has been actively debated for more than three decades (Mokhtarian, 2003; Pawlak et al., 2020; Salomon, 1986). Beyond the expected substitution impact, other first order effects such as complementarity, modification, neutrality, multitasking and activity fragmentation are also possible (Hubers et al., 2018; Kenyon and Lyons, 2007; Salomon, 1986). In the long run, ICT can also produce impacts of higher order, such as changes in household location choice and in individual values and beliefs, which might in turn yield additional effects on mobility patterns (Salomon and Mokhtarian, 2007).

Regarding work trips, most of the studies published until the late 1990 s forecasted large substitution effects originated from teleworking (Salomon, 1998). However, from the 2000 s onwards, research using

* Corresponding author at: Trabalhador São-carlense Avenue, 400, São Carlos, State of São Paulo 13566-590, Brazil.
E-mail addresses: jorge.ubirajara@usp.br (J.U. Pedreira Junior), cirapitombo@usp.br (C.S. Pitombo).

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robust survey data found that complementary effects from teleworking were significant (Salomon and Mokhtarian, 2007; Zhu et al., 2018). Indeed, although the effect of teleworking on work trips are predominantly of substitution (Andreev et al., 2010), there is rich evidence of the generation of additional trips for other purposes (He and Hu, 2015; Kim, 2016; Kim et al., 2015; Zhu, 2012; Zhu et al., 2018). Reasons for this fact stem mainly from the association of teleworking with distant and low-density household location choices, as well as the time and cost savings that could be allocated for other activities and trip purposes (Mokhtarian, 2009).

Also relevant in this context is the investigation of the accessibility factors that influence individuals' decisions on how to carry out their activities (either in-person or remotely). From the physical accessibility perspective, there are the land-use and transportation aspects associated with the built environment that impact the potential of an individual to reach spatially dispersed opportunities (Páez et al., 2012). On the other hand, virtual accessibility factors as the amenability of an activity to be performed remotely, the possession of an ICT device, having adequate Internet access and the ability to use a gadget and its functionalities are also known to guide this decision (Lavieri et al., 2018). Notably, the COVID-19 pandemic added a new element to the phenomenon, as the individuals' risk perception to contagion severely affected their activity-travel behavior (Brewer et al., 2007; Calderón Peralvo et al., 2022; Paul et al., 2022).

Considering this background, the present study proposes an investigation of the COVID-19 pandemic effects on work trips and teleworking in Brazil using an online longitudinal survey structured in two waves of collection. In the first wave, distributed in the second half of 2020, we aimed at identifying substitution patterns of work trips by teleworking by comparing the 2nd half of 2020 to the pre-pandemic period (early March 2020) and computed their associations with sociodemographic factors and accessibility measures (both physical and virtual). One year later, we ascertained how activity-travel behavior changed for each of these groups considering a more controlled epidemic scenario in the second wave of data collection.

It is important to highlight that we consider telework as work done remotely from any place other than the workplace (albeit due to the pandemic restrictions throughout the pandemic, this place was predominantly the individuals' households). Accordingly, this research contributes to the debate by providing a more detailed measure of the substitution patterns identifying different levels of the phenomenon (no or low substitution, moderate substitution and intense substitution). Indeed, most studies investigating the impacts of the COVID-19 pandemic on activity-travel behavior considered changes only in either teleworking or work trips, but not both variables, which must be jointly addressed to characterize the substitution phenomenon. Additionally, we outline important differences between these groups that serve as important inputs for the design of urban policies in a post-pandemic scenario or in eventual future crises.

This paper is divided into five sections including this Introduction. Section 2 discusses the empirical findings of the research related to teleworking and travel behavior during the pandemic and the scientific gaps to be addressed. Next, Section 3 approaches the methodological procedure to attain the research objectives. Then, Section 4 presents and discusses the results and their policy implications. Finally, Section 5 draws the main conclusions and sets out the scenario for future work.

2. Literature review

Following the first wave of the COVID-19 pandemic, circulation restrictions were imposed worldwide. To prevent activities from being completely interrupted, several organizations directed their human resources to work from home. As expected, researchers throughout the globe tried to closely monitor this phenomenon. Indeed, considering the first two years of the pandemic (2020 and 2021), the teleworking experience was extensively investigated as more than 995 articles have been published about this topic, corresponding to an almost 50% rise in scientific production with respect to the previous years (Mamani-Benito et al., 2022). More than 3/4 of these studies were published as original manuscripts and nearly 85% of this total was conducted in only 15 nations (United States, India, the United Kingdom, Italy, Australia, Indonesia, Spain, the Netherlands, France, China, Canada, Romania, Germany, Japan and Malaysia).

Notably, investigations in countries from North America, Western Europe and Eastern and East and Southeast Asia substantially outnumbered those in nations from other regions such as Latin America, Sub-Saharan Africa and the Middle East. According to Mamani-Benito et al. (2022) and Benita (2021), a number of sub-themes can be identified in studies on teleworking and transport activities during the pandemic, and the present paper further develops the topics cross-sectional and longitudinal studies on teleworking and protective behavior and work from home. Important discussions around these aspects lie on quantifying the influence of the factors that drive individuals' behaviors and how to measure the substitution of work trips by teleworking, which are discussed in more detail subsequently.

2.1. *Factors affecting teleworking and travel behavior during the COVID-19 pandemic*

As mentioned earlier, several factors may affect teleworking and traveling, especially during the COVID-19 pandemic. The following sections illustrate the main findings regarding how activity-travel behavior in this time was related to sociodemographic factors, characteristics of occupations, pandemic risk perception, the built environment and ICT engagement.

2.1.1. *Job characteristics*

Regarding work activities, a major aspect influencing activity-travel behavior is the nature of the tasks in each type of occupation. In a job classification study, it was found that roughly 37% of the occupations in the United States could be done entirely from home, in which Luxembourg presents the highest value (53.4%) and Mozambique is the country where it was hardest to find teleworkable occupations (5.2%) (Dingel and Neiman, 2020). Considering the labor market in Brazil, only a quarter of the jobs can be done entirely from home, but it also varies considerably across Brazilian states. In the Federal District (from the Center-West region), 31.5% of the jobs are amenable to telework, whereas only 15.6% of the workers from the state of Piauí (from the Northeast region) can work from home (Góes et al., 2020).

These differences reflect great socioeconomic disparities between these states, mainly associated with a higher level of informal jobs present in the latter (Rodrigues da Silva et al., 2023) and a higher concentration of public officials in the former, whose mobility was extensively affected by the pandemic (Pedreira Junior et al., 2022). In fact, these global differences were further confirmed in empirical studies concerning telework undertaken during the pandemic. Results from an international survey conducted in 14 countries found that from 60% to 80% of those professionals whose jobs were amenable to telework actually did so, as opposed to 30% of those whose jobs were not (Shibayama et al., 2021). Other studies found that individuals engaged in teaching and managerial positions worked more from home than health professionals and blue-collar workers (Borkowski et al., 2021; Fatmi et al., 2021; Olde Kalter et al., 2021; Salon et al., 2022).

2.1.2. *Sociodemographic factors*

Jobs that can be done entirely from home usually pay more and are more common in countries with higher GDP per capita (Dingel and Neiman, 2020), which indicates that some of the existing inequalities are expected to increase with the crisis. Overall, American workers in households with incomes over $100,000 were more likely to have the option to telework (Salon et al., 2022). It was also found that poorer and part-time employees faced more unemployment during the pandemic in

Chicago-USA (Shamshiripour et al., 2020), whereas wealthier individuals did more teleworking and also more teleshopping in Indonesia (Irawan et al., 2021). In Malmö, Sweden, individuals living in more prosperous neighborhoods not only did more teleworking, but also adapted faster to it than those in poorer districts (Bohman et al., 2021). Furthermore, as expected, there was a strong correlation between jobs amenable to teleworking and the level of education of the individuals (Fatmi et al., 2021; Reiffer et al., 2022; Salon et al., 2022; Shibayama et al., 2021), given the additional years of instruction that these occupations often require.

With respect to gender differences, the findings are context-specific. For example, German women were less involved with telecommuting than men (Reiffer et al., 2022), which could be attributed to the heterogeneity in gender distributions across occupations. However, it was also found that Dutch and Canadian women tended to prefer working from home when facing longer commuting distances (Kroesen, 2022; Rahman Fatmi et al., 2022). Females were also less likely to travel and engage in out-of-home activities (Fatmi et al., 2021; Irawan et al., 2021), probably due to a greater risk perception within this group (Parady et al., 2020). These aspects shed light on the disproportionate decrease in activity participation (either physical or virtual) among women during the pandemic, which could be widening the existing gender inequality in the society. Finally, age differences were also encountered, as older individuals were more inclined to telecommute and be more satisfied with remote work (Hiselius and Arnfalk, 2021; Salon et al., 2022), although younger and middle-aged individuals also reduced more out-of-home activities during the pandemic (Fatmi et al., 2021).

2.1.3. Pandemic risk perception

The role of risk perception in shaping activity-travel behavior was also an important topic of research during the pandemic. Admittedly, findings from previous epidemic crises indicate that risk perception is key in determining behavior, such as getting vaccinated and avoiding risky situations (Brewer et al., 2007; Sadique et al., 2007). In the COVID-19 context, risk perception was found to be negatively associated with the frequency of out-of-home activity and positively associated with teleworking (Irawan et al., 2021; Nguyen, 2021; Parady et al., 2020). Individuals who took the risk more seriously also reduced more trips for all purposes in Indonesia (Shakibaei et al., 2021) and spent less time traveling in Poland (Borkowski et al., 2021). In association with sociodemographic factors, females and individuals with more years of education tended to adopt more preventive measures in their routines (Borkowski et al., 2021).

A remarkable (and ubiquitous) finding refers to the higher perceived risk associated with public transit, which significantly impacted bus and train ridership. In a study conducted in 14 countries during 2020, it was found that more than 70% of public transit use reduction occurred due to a greater risk perception associated with this travel mode (Shibayama et al., 2021). Another study conducted in 10 European nations revealed that when measures were eased, car use and walking practically came back to normal, while public transit still lagged far behind pre-pandemic figures (Monterde-i-Bort et al., 2022). As a matter of concern, a systematic review of 56 studies confirmed that due to the apprehension on viral transmission, this reduction was also accompanied by an increase in private vehicle use (Paul et al., 2022). The situation seems to be even worse when looking at individuals' intentions after the pandemic, as half of British public transit users reported that they might switch mode once restrictions were lifted (Harrington and Hadjiconstantinou, 2022).

2.1.4. Built environment and ICT engagement

The effects of the built environment and ICT engagement in activity-travel behavior during the pandemic were less studied than the previous factors. With respect to the former, Mouratidis and Peters (2022) have shown that teleworking and virtual meetings increased to a greater extent in Norwegian denser neighborhoods, which was also observed in the USA (Salon et al., 2022). Mouratidis and Peters (2022) also demonstrated that higher public transit accessibility (measured as the number of stations within a 1 km radius from the individual residence) changed from being negatively associated with teleworking before the pandemic to having no association at all during the crisis. This indicates that the ease to reach the workplace provided by an increased public transit access was probably offset by the higher risk perception of traveling using this travel mode. On the other hand, the number of local facilities within a 1 km radius remained positively correlated to telework even during the COVID-19 pandemic as it was before. In this case, the authors argue that this could be either due to some of these local facilities remaining open during the pandemic and/or due to habits and attitudes of residents living in such areas.

Finally, studies measuring the influence of virtual accessibility on activity-travel behavior during the COVID-19 pandemic are considerably scarcer. Although the ability to conduct work activities remotely were satisfactorily accounted for, other aspects such as the ownership of (adequate) ICT device(s), the subscription and coverage of a network provider and the proficiency and engagement with ICT gadgets and services (Lavieri et al., 2018) were not adequately addressed. Research that attempted to gauge these effects are worth mentioning though. A study conducted by Irawan et al. (2021) found that more experience in the use of ICT devices is associated with lower levels of out-of-home activity in Indonesia. On the other hand, Nguyen (2021) demonstrated that the number of hours spent on the Internet by Vietnamese people was neither correlated with working entirely from home nor with the appraisal of teleworking. Likewise, no effect of higher speed Internet on teleworking was observed in the USA (Salon et al., 2022). Indeed, although the frequency of ICT use or experience might be a relevant metric, this may be singly insufficient to describe the role of virtual accessibility. It might also be the case that after accounting for the job's amenability to telework, people more cognitively engaged and/or proficient with ICT are more willing to work remotely. As has been demonstrated in several contexts, ICT literacy plays a crucial role in enabling individuals to use digital technology to manage, integrate, evaluate and create information in a knowledge society (Zylka et al., 2015).

Considering the studies mentioned in this literature review, a synthesis of the most important findings relating each group of factors to activity-travel behavior and teleworking during the pandemic can be seen in Table 1.

2.2. Methodological challenges in measuring substitution of work trips by teleworking

Several methodological strategies have been adopted to measure the impact of the pandemic on (work-related) activity-travel behavior since 2020. Data collection was mainly structured with longitudinal surveys, either designed during the pandemic (Salon et al., 2022; Shakibaei et al., 2021; Shamshiripour et al., 2020) or corresponding to new waves of pre-existent institutional panels, such as the German Mobility Panel (Reiffer et al., 2022), the Netherlands Mobility Panel (de Haas et al., 2020) and the Dutch Mobile Mobility Panel (Olde Kalter et al., 2021). Nevertheless, both cross-sectional (Irawan et al., 2021; Jou et al., 2022; Mouratidis and Peters, 2022) and pooled cross-sectional (Beck et al., 2020) designs were also undertaken. For all those surveys started during the pandemic (either longitudinal or cross-sectional), researchers relied on retrospective questions regarding the habit of travel and/or teleworking before the pandemic to measure the changes. Despite the likely recalling bias these studies may be incurring, the untimely nature of the crisis prevented most of the research from being carried out in any other way. Regarding the instrument, practically all studies used self-reported questionnaires, and some of them were combined with travel diaries (de Haas et al., 2020; Reiffer et al., 2022). An interesting case involved the tracking of individuals' smartphones through GPS data, wherein trip attributes such as origin, destination, distance and travel mode were automatically obtained from processing routines on the raw data (Olde

Table 1
Main findings from the literature review regarding each group of factors.

Factors	Findings	References
Job characteristics	- As expected, individuals in occupations more amenable to telework worked more from home during the pandemic.	(Borkowski et al., 2021; Dingel and Neiman, 2020; Fatmi et al., 2021; Góes et al., 2020; Olde Kalter et al., 2021; Pedreira Junior et al., 2022; Rodrigues da Silva et al., 2023)
Sociodemographic attributes	- Higher socioeconomic status and more years of education associated with more teleactivity frequency. Relationships with gender and age are context specific.	(Bohman et al., 2021; Fatmi et al., 2021; Hiselius and Arnfalk, 2021; Irawan et al., 2021; Kroesen, 2022; Nguyen, 2021; Parady et al., 2020; Rahman Fatmi et al., 2022; Reiffer et al., 2022; Salon et al., 2022; Shamshiripour et al., 2020; Shibayama et al., 2021)
Pandemic risk perception	- Higher risk perception correlated with increased teleworking frequency and less travel (mainly by public transit).	(Borkowski et al., 2021; Harrington and Hadjiconstantinou, 2022; Irawan et al., 2021; Monterde-i-Bort et al., 2022; Nguyen, 2021; Parady et al., 2020; Paul et al., 2022; Shibayama et al., 2021)
Built environment and ICT engagement	- Overall, denser neighborhoods are positively associated with teleworking. Conflicting or no evidence regarding the relationship of ICT use/ experience and Internet quality with teleworking.	(Irawan et al., 2021; Mouratidis and Peters, 2022; Nguyen, 2021; Salon et al., 2022)

Kalter et al., 2021).

The modeling approaches to measure change also varied considerably. First, it is worth mentioning that most studies modeled only one of the two variables of interest, i.e., either the teleworking frequency (Mouratidis and Peters, 2022; Rahman Fatmi et al., 2022; Salon et al., 2022; Shakibaei et al., 2021; Shamshiripour et al., 2020) or the work trip frequency (Irawan et al., 2021; Jou et al., 2022). Overall, researchers adopted multivariate models for each of wave of collection or created features to directly represent the level of change. Although modeling only teleworking or work trips provides important answers regarding the phenomenon, this approach is unable to precisely assess the magnitude of the substitution. Admittedly, quantifying an increase in the teleworking frequency does not guarantee that this same amount was reduced in work trips (the reverse is also true). Some research, however, managed to give an approximate answer to this question by distinguishing among “new telecommuters”, “experienced telecommuters” and those who “never telecommuted” (Reiffer et al., 2022; Salon et al., 2022; Shamshiripour et al., 2020). Furthermore, this classification carries some sort of arbitrariness with it. For example, individuals who worked from home once a week fall into the same category as those who telecommuted every day before the pandemic (i.e., the “experienced telecommuters” category). Likewise, the “new telecommuters” group consist of both individuals who telecommuted a few days a week and by those who did it every day during the pandemic, as long as they did not work from home before the pandemic. Although understanding these classifications are useful to design tailored policies for each group, they fail to give a more precise answer about the impacts of the COVID-19 on mobility.

Finally, studies that attempted to model the relationships between teleworking and work trips did so by considering the first as an exogenous variable to the latter. Reiffer et al. (2022) adjusted a multivariate linear regression considering the difference in the number of trips

Table 2
Survey design of the studies and whether they investigated the substitution phenomenon.

Study	Survey Design Longitudinal	Cross-Sectional	Pooled Cross-Sectional	Investigated the relationship between changes in work trips and in telework
(Beck and Hensher, 2020)			X	X
(de Haas et al., 2020)	X			
(Fatmi et al., 2021)		X		
(Irawan et al., 2021)		X		
(Olde Kalter et al., 2021)	X			X
(Mouratidis and Peters, 2022)		X		
(Reiffer et al., 2022)	X			X
(Salon et al., 2022)	X			
(Shamshiripour et al., 2020)	X			
(Shakibaei et al., 2021)	X			

between 2020 and 2019 as the dependent variable and age, commuting distance, public transit use, car use and the telecommuting classification as the independent variables. As expected, the telecommuting classification proved to be a significant factor, in which new telecommuters reduced more trips than experienced telecommuters. Olde Kalter et al. (2021) and Beck et al. (2020), in turn, used a sequential approach to attain this goal. The former adjusted an ordinal logistic regression to explain the variation in telecommuting frequency and then used this variation as an independent variable to model the intention to reduce car use after the pandemic with a binomial logistic regression. The authors have shown that changing the telecommuting frequency was not an important predictor of the intention of reducing car trips, proving that being an experienced or a new telecommuter might not influence car use in the Netherlands after the crisis. Similarly, Beck et al. (2020) first applied an ordinal logistic regression to model the number of days per week individuals work from home and used the resulting fitted probabilities as an independent variable in two Poisson regression models, considering the number of one-way weekly commuting trips by car and by public transit. In this case, not working from home was positively correlated with car use both in Wave 1 (Apr/2020) and in Wave 2 (May-Jun/2020) of the data collection. Interestingly, traveling every day was negatively correlated with public transit in the first wave, but positively correlated in the second. The authors claim that this could be credited to the alleviation in public transit restrictions made by the Australian government in the transition from one period to another.

A summary of the survey designs of each study and whether they invested in modeling the relationship between changes in work trips and in teleworking is given by Table 2.

2.3. Research gaps and opportunities

Considering this background, the present study aims at addressing three important research gaps. First, few studies tried to directly quantify the substitution of work trips by teleworking caused by the COVID-19 pandemic (Beck and Hensher, 2020; Olde Kalter et al., 2021; Reiffer et al., 2022). For the ones who (explicitly or not) tried to measure it, the metrics associated with teleworking frequency were considered as exogenous to the work trip frequency. This modeling choice might pose some serious endogeneity issues to the analysis, as both outcomes should be seen as a joint package of decisions that each individual makes in the allocation of his/her time budget (Lavieri et al., 2018). Second, these outcomes are influenced by several factors, including measures of virtual and physical accessibility, which have not been systematically addressed by the studies in the literature. Specially with respect to virtual accessibility, to the best of the authors' knowledge, no study has measured cognitive aspects associated with ICT engagement and proficiency, which might influence individuals' willingness to perform activities either remotely or in-person even after accounting for the "teleworkability" of the job duties. Third, there is a strong geographical imbalance in the number of studies conducted throughout the world, as have been demonstrated in the beginning of this section, with a lower number of publications in the Global South context.

3. Materials and method

3.1. Survey design

To understand activity-travel behavior changes related to work activities, a panel data was collected for 2020 and 2021. The questionnaire for the first wave (2020) was designed based on a literature review concerning ICT and travel behavior both before and during the pandemic and improved after a pilot survey with 10 individuals. This survey was distributed in a snowball fashion via social media accounts on Twitter, Instagram and Facebook, from September 19 to October 18, 2020. Since this non-probabilistic sampling method is likely to incur in sampling bias, the results were not extrapolated to the Brazilian population and the conclusions were solely drawn to the sample under study. However, due to the longitudinal nature of the data, relevant information regarding within-individual changes can be revealed with this type of data collection. Indeed, although this limitation is fairly common in the literature on ICT and travel behavior, previous studies have produced valuable findings (Ben-Elia et al., 2014; Kenyon, 2010; van den Berg et al., 2013), even with some of them relying on cross-sectional designs to adjust their models. Other studies also adopted web-surveys during the pandemic, adopting the same or similar distribution strategies to conduct their research (Fatmi et al., 2021; Jou et al., 2022; Rahman Fatmi et al., 2022; Shakibaei et al., 2021).

In the present study, 702 valid and complete answers have been collected in this first wave, including retrospective questions relative to their situation both before the pandemic in Brazil (early March 2020) and during the period of collection (from September 19 to October 18, 2020). These two periods of analysis are referred to as t_0 and t_1, respectively. Given that the interest lies in work activities, a subset of the sample of those who were working in the period of collection (t_1) and that were neither unemployed, retired nor on furlough before the pandemic (t_0) were selected for analysis, resulting in 524 individuals. In the second wave of data collection (ranging from October 6 to November 5, 2021), the same group of individuals were contacted via e-mail to answer questions regarding their teleworking frequency and travel behavior at the time of collection. This period was called t_2 and gathered answers from 192 individuals, a rate of response of 27.4% with respect to the initial panel size. This result is in line with the expected response rates in this kind of study, which ranges from 10% to 25% (Sauermann and Roach, 2013). For the sake of comparison, the institutional COVID Future Panel survey carried out in the United States managed to collect responses from 1/3 of their initial panel in subsequent waves (Salon et al., 2022). From the 192 individuals who responded to the second wave in our study, 152 consisted of individuals who were working at the time of collection. The details about the variables used in the study, the methodological procedure and the sample characteristics are presented in Sections "3.2. Variables of the study", "3.3. Method" and at the beginning of "4. Results and Discussion", respectively.

Fig. 1 illustrates the periods of data collection contrasted with the change in workplace movements in Brazil concerning a pre-pandemic scenario, obtained from Google Mobility Reports, for 2020 and 2021 (Google LLC, 2021). In the first wave of collection, COVID deaths in Brazil were decreasing steadily (Fig. 2), which were followed by a progressive re-opening of some activities (Fig. 1). As compared to Europe and the United States, the Brazilian first wave of the pandemic started much later due to early restrictions mandated by local authorities. However, the lack of coordination between national and subnational government levels to implement stricter and standardized plans resulted in a longer duration of this first wave in Brazil when compared to other places (Touchton et al., 2021).

During the second wave of data collection, the situation was considerably milder in Brazil due to the rapid vaccination rate. Indeed, from the start to the end of this period (October 6 to November 5, 2021), the percentage of Brazilians fully vaccinated grew from 45.2% to 55.9%

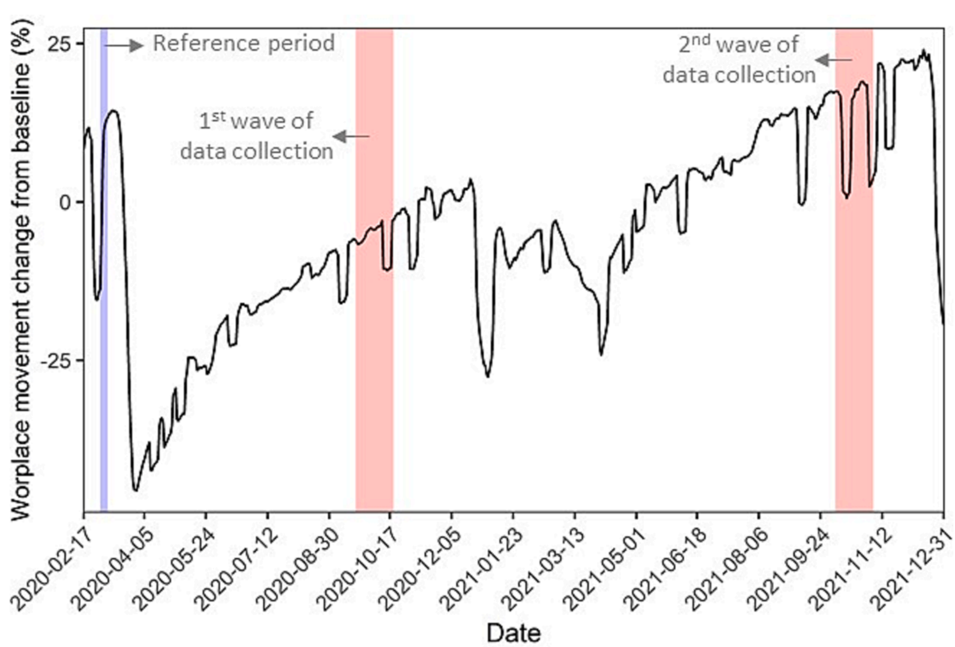

Fig. 1. Median change in workplace movements in Brazil with respect to January 2020 Source: Google Mobility Reports (Google LLC, 2021).

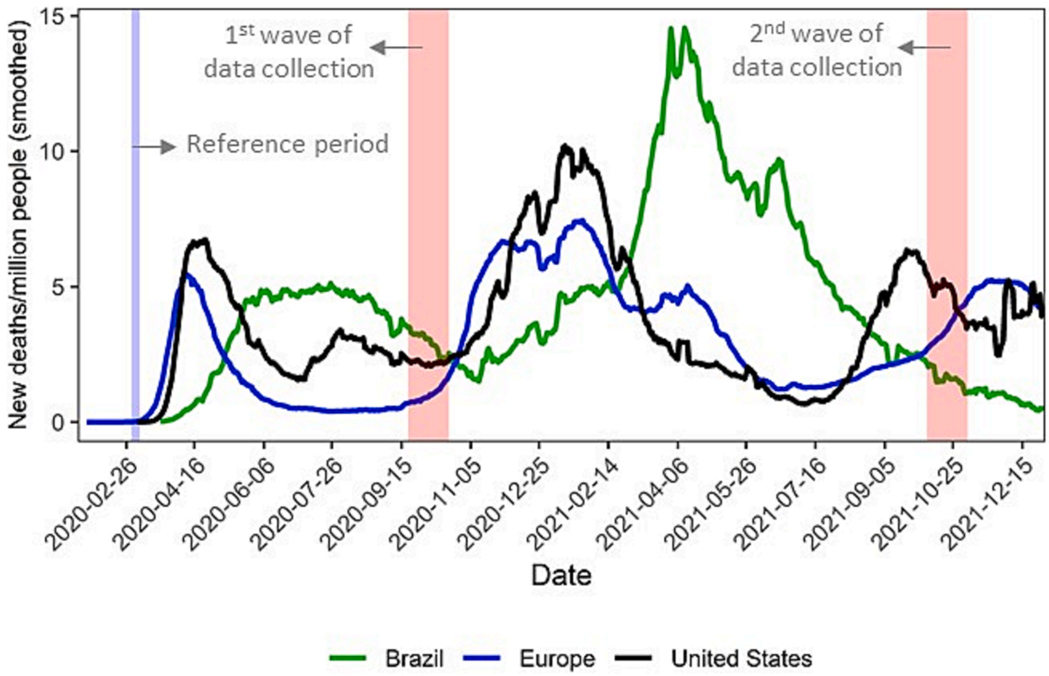

Fig. 2. 7-day moving average of new deaths in 2020 for Brazil, Europe and the US Source: Our World in Data (Ritchie et al., 2022).

(Ritchie et al., 2022). At this moment, workplace movements were even higher than the baseline scenario measured in Google Mobility Reports. Therefore, it represents an interesting point of evaluation of the endurance of the mobility patterns originated during the pandemic.

3.2. Variables of the study

From the survey of the first wave of data collection, a dataset consisting of sociodemographic attributes, work trips and teleworking habits and also factors associated with physical and virtual accessibility was prepared. Most of these variables were measured for the periods t_0 and t_1, whose details are shown in Table 3. Accessibility measures – groups d) and c) from Table 3 – were devised based on the suggestions of Lavieri et al. (2018). In the second wave of data collection (encompassing t_2), only the frequency of work trips, the travel mode choice and the frequency of teleworking were measured, thus allowing the monitoring of the individuals' activity-travel behavior after one year.

Considering general sociodemographic factors, as well as common measures such as age, gender, education and the city of residence, aspects related to the working attributes of the individual were also measured. First, individuals indicated how much interruption of in-person working they faced because of the pandemic (either enforced by government regulations or by specific policies from their companies). Then, the characteristics of the occupations were also assessed through a multiple selection of an 18-item list of aggregated work tasks (Table 4), developed for the Brazilian labor market by the Brazilian Institute for Applied Economic Research (Reis, 2016).

Following a similar logic of classification developed in previous studies (Dingel and Neiman, 2020; Góes et al., 2020), we considered activity types from 1 to 9 as amenable to teleworking, whereas 10 to 18 were regarded as not amenable to teleworking. Since the respondents could choose multiple groups of activities, the "teleworkability" of the individual's occupation was defined as the ratio between the number of activities amenable to teleworking and the total number of activities in their routines. For example, an individual who defined his/her occupation as comprising activity types 1 (Research, analyze, evaluate develop), 5 (Teach) and 12 (Repair, renovate, reconstruct) would result in the teleworkability level of 2/3.

Travel behavior was evaluated by the frequency of work trips and the predominant travel mode used. Some potential measures of physical accessibility were also considered in the study. First, individuals were asked about how easy it was to travel without a car (to work, shop in-person and eat out), the quality of the transportation infrastructure in their neighborhood (sidewalks, road pavement and bikeways) and car ownership. They were also asked about the duration of the walking trip to the nearest grocery from their homes. The effects of the pandemic on the attractiveness of each travel mode were also evaluated by asking the individuals about their perceived likelihood of being infected by COVID-19 when using different travel modes (public transit, private car, motorcycle, walking, cycling, ridesourcing). Given that each respondent also indicated the mode choice for work trips, a variable indicating the perceived probability of the travel mode used to travel before the pandemic was considered for analysis.

Individuals also had to answer how often they teleworked and about aspects of virtual accessibility. The latter was assessed with questions involving device ownership (personal computer, smartphone and tablet computer), perceived quality of the household Internet access, ICT cognitive engagement and ICT proficiency. To evaluate the ICT cognitive engagement, five items concerning positive self-concept and interest in ICT were drawn from the scale developed by Zylka et al., (2015), which was successfully implemented in multiple contexts on educational research (Kunina-Habenicht and Goldhammer, 2020; Meng et al., 2019; Nikolopoulou and Gialamas, 2016). Finally, ICT proficiency was measured by two aspects, the ability of using virtual meeting platforms and the ability of using virtual management tools for working/learning purposes. Only measures for t_1 of ICT cognitive engagement and ICT proficiency were considered in the analytical process.

3.3. Method

The methodological procedure comprised the workflow depicted in Fig. 3, wherein the stages of questionnaire design and data collection were described in the previous sections. The data consisting of the first wave of data collection (measurements of t_0 and t_1) were analyzed using a two-step method. In the first step, physical and virtual accessibility measures were derived from the data by obtaining principal components from a nonlinear dimensionality reduction technique. Then, a latent class regression model was carried out to identify the substitution

Table 3
Description of the variables of the study.

Group	Variable$^{\text{period of measurement}}$ (0,1,2)	Scale	Levels/Description
a)	Age[1]	Ordinal	18–49 (young and middle-aged adults), 50 or more (older adults)
	Gender	Nominal	Female, male
	Education[1]	Ordinal	No degree, undergraduate degree, graduate degree
	Moved from one city to another	Nominal	No, Yes
b)	In- person job interruption status[1]	Ordinal	Not interrupted, partially interrupted (hybrid regime), fully interrupted
	Teleworkability level of the occupation[0,1]	Continuous	Proportion of teleworkable activities in the individual's pool of duties based on a multiple selection from an 18-aggregate group of activities*
c)	Travel frequency (work trips)[0,1,2]	Ordinal	Not applicable/never/rarely, less than 4 times a month, once a week, 2 or 3 times a week, 4 or more times a week
	Travel Mode (work trips)[0,1,2]	Nominal	Public transit, private car, motorcycle, walking, cycling, ridesourcing
d)	Ease of traveling without a car (for working, shopping and eating out purposes)	Ordinal	Very hard, hard, normal, easy, very easy
	Quality of transportation infrastructure in the neighborhood (sidewalks, road pavement, bikeways)[0,1]	Ordinal	Very poor, poor, fair, good, very good
	Walking time to the nearest grocery[0,1]	Ordinal	0–5, 6–10, 11–15, 16–20, 21–30, 31–40, 41–50, 51–60, 61 or more (minutes)
	Car ownership[0,1]	Nominal	No, yes
	Perceived probability of COVID-19 infection with respect to the travel mode of work trips before the pandemic[1]	Ordinal	Very low, low, medium, high, very high
e)	Teleworking frequency[0,1,2]	Ordinal	Not applicable/never/rarely, less than 4 times a month, once a week, 2 or 3 times a week, 4 or more times a week
f)	Device ownership (personal computer, tablet computer, smartphone)[0,1]	Nominal	No, yes
	Household internet quality[0,1]	Ordinal	Very poor, poor, fair, good, very good
	Confidence in handling with computers (ICT Cognitive Engagement #1)[1]	Ordinal	Strongly disagree, disagree, neutral, agree, strongly agree
	Ability to solve computer problems (ICT Cognitive Engagement #2)[1]		
	Ability to learn new computer programs (ICT Cognitive Engagement #3)[1]		
	Preference of working using a computer (ICT Cognitive Engagement #4)[1]		
	Interest in the launching of new computer technologies (ICT Cognitive Engagement #5)[1]		
	Proficiency in using virtual meeting platforms (ICT Proficiency #1)[1]	Ordinal	Very low, low, medium, high, very high
	Proficiency in using work/e-learning management platforms (ICT Proficiency #2)[1]		

Legend: a) Sociodemographic factors (general); b) Sociodemographic factors (work-related); c) Work trip habits; d) Physical accessibility measures; e) Teleworking habits; f) Virtual accessibility; *According to the aggregation of occupations in Brazil performed by (Reis, 2016); [0] early March 2020 (before the pandemic); [1] from 19th September to 18th October 2020; [2] from October 6 to November 5, 2021.

Table 4
Groups of activities that characterize the individuals' occupations.

Item	Group of activities
1	Research, analyze, evaluate, develop
2	Design, plan, sketch
3	Execute or interpret laws/rules
4	Employ or manage personnel, lobby, organize, coordinate
5	Teach
6	Sell, buy, advise clients, advertise
7	Publish, present, entertain others
8	Calculate, do bookkeeping, control financial resources
9	Correct text or data, program, register information, organize documents
10	Measure, quality control, perform laboratory tests
11	Equip or operate machines
12	Repair, renovate, reconstruct
13	Cultivate
14	Manufacture, install, construct, mold materials, cook, build
15	Cleaning
16	Pack, ship or transport products
17	Serve, accommodate, nurse or treat others
18	Secure

Source: (Reis, 2016).

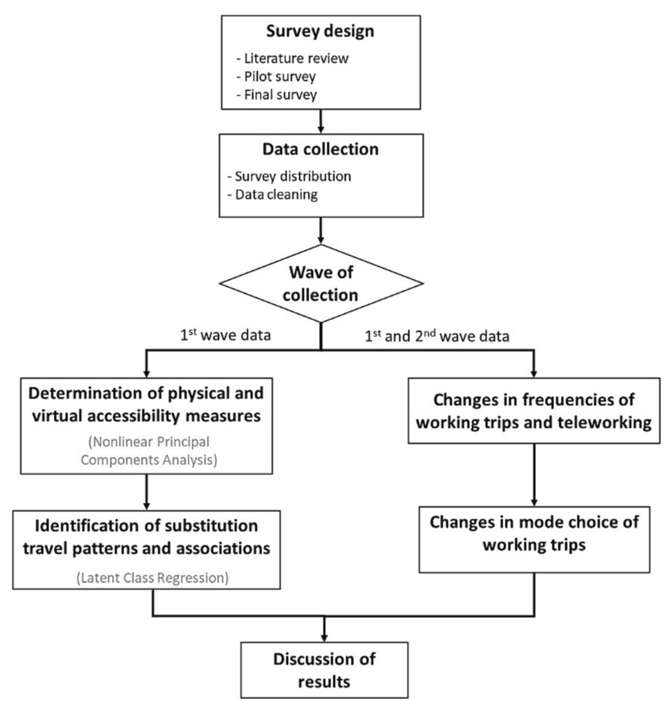

Fig. 3. Methodological procedure.

patterns of work trips by teleworking and their relationships with sociodemographic attributes and the previous principal components. Considering the substitution classes formed with the first wave of data collection, the changes in frequencies of work trips and teleworking and in travel mode choices of these trips were visually analyzed with Sankey plots using data from both waves (encompassing the periods t_0, t_1 and t_2). Finally, the results from these analytical steps and their implications were discussed.

3.3.1. Determination of physical and virtual accessibility measures

To determine physical and virtual accessibility measures, a dimensionality reduction technique was performed with the physical and virtual accessibility measures (variables from groups "d" and "f" from Table 1). The reasons why this procedure was chosen is two-fold. First, considering that most of these variables are likely correlated with each other, representing virtual and physical accessibility factors with a reduced number of orthogonal (and meaningful) components avoids multicollinearity and allows for a higher number of observations per variable. Second, given that all these variables are categorical (either ordinal or binary) and that traditional principal component analysis is applied only to numeric variables, a nonlinear principal components analysis (NLPCA) was undertaken (Meulman et al., 2004). This method has been successfully explored in other transportation studies, such as modeling driver's behavior (Campos et al., 2021), public transit user's satisfaction (Chica-Olmo et al., 2018) and road traffic accident severity (Chung and Song, 2018).

NLPCA works by defining an appropriate quantification of the levels of the original categorical variables and finding the principal components resulting from these transformed variables (Linting et al., 2007). The process consists of minimizing a loss function in the form of $\boldsymbol{SSQ}(Y-XB')$, where $\boldsymbol{SSQ}$ is the sum of squares operator Y, X and B are the matrices of quantified variables, components and loadings, respectively (de Leeuw, 2013). Given that both the quantification and the parameters of the principal components analysis are unknown, this problem is solved iteratively with an alternating least squares procedure. The algorithm starts with randomly assigned principal component parameters. Next, the variables are transformed with appropriate quantification functions in a step called optimal scaling. Then, the components are evaluated from the transformed variables. These last two steps alternate until the loss function is minimized. For more details on the mathematical formulation of the problem, the reader is referred to the specialized literature (de Leeuw, 2013; Gifi, 1990).

The types of transformations applied to the variables in NLPCA are known as "analysis levels" (Linting et al., 2007) and entail distinct restrictions to the quantification procedure. The most constrained transformation is the "numeric analysis level", by which not only the order, but the spacing between consecutive categories of the variable are maintained. At an intermediate level of restriction, the "ordinal analysis level" allows for different spacing between consecutive levels of the variable, but guarantees that the quantification occurs in a monotonically nondecreasing way. Finally, the less restrictive transformation is the "nominal analysis level", whereby the levels of the original variable can assume any value, with no order restrictions. The latter allows nonlinear relationships between variables to be represented by the principal components (such as a quadratic relationship between age and income, in a context where younger and older individuals earn less than other adults).

The current analysis considered an ordinal analysis level to perform the variable quantification. The implementation was carried out with the Gifi package for the R programming language (Mair et al., 2019). It should be noted that the numeric values assigned to the original levels of the variables are stable across observations. For instance, all individuals that answered "very easy" to the question "how easy is it for you to travel to work without a car?" have the same numeric value for the corresponding variable. The nominal variables considered in the study are associated with technological device and vehicle ownership, which have been measured in a binary fashion (No/Yes). Therefore, positive loadings from these variables on a specific component indicate higher possession of such type device or vehicle, whereas negative values imply the opposite interpretation.

Unlike linear principal components analysis (PCA), NLPCA solutions are not nested for successive values of m (Linting et al., 2007). This means that a solution with m dimensions might differ from another with $m+1$ components. Therefore, to choose the best m, the stability of the solutions for a scree test criterion with $m-1$, m and $m+1$ must be evaluated. Finally, those principal components with eigenvalues greater than one and not sharing loadings higher than 0.4 across variables were considered for the next analytical step.

3.3.2. Identification of substitution patterns in work trips

The substitution travel patterns were determined by considering the frequency of work trips and teleworking both before (t_0) and during the pandemic (t_1) for the sample of 524 working individuals. To achieve this goal, a Latent Class Regression (LCR) model was adjusted to the data. LCR is a special case of Latent Class Analysis (LCA), a model-based clustering technique wherein latent heterogeneity in the data can be revealed (Clogg and Goodman, 1984; McCutcheon, 1987). LCA finds individual membership through unobserved (latent) classes associated with response patterns from a set of observed (indicator) survey items (Andersen et al., 2003). As this method produces a latent categorical variable from observed categorical variables, it is usually viewed as a categorical analog of factor analysis (Bartholomew et al., 2011). As it is a probabilistic technique, it usually outperforms deterministic clustering methods (such as K-Means) by producing lower misclassification errors and better guidance on choosing of the number of classes through goodness-of-fit statistics (Vermunt and Magidson, 2002).

LCR extends the traditional LCA application by allowing covariates to predict class membership in the data (Dayton et al., 1988). This technique has been tested in many travel behavior applications, such as finding patterns of multi-modal urban traveling and measuring attitude toward travel modes (Clark et al., 2021; Kroesen, 2014; Molin et al., 2016). In the present study, we considered the sociodemographic attributes from groups "a" and "b" from Table 3 and the principal components from the previous steps as the model's covariates.

LCR involves the simultaneous estimation of two models (namely, the measurement and the structural models), represented by Equations (1) and (2). Formally, considering a sample with individuals $i=1,\cdots n$, indicator variables $j=1,\cdots,J$ (each having alternatives $r_j=1,\cdots,R_j$), the posterior probability that an individual i responded $\boldsymbol{y}_i$ (given that the $\boldsymbol{x}_i$ covariate vector was observed) can be estimated by:

$$P(\boldsymbol{Y}=\boldsymbol{y}_i|\boldsymbol{X}_i=\boldsymbol{x}_i)=\sum\nolimits_{c=1}^{K}\gamma_c(\boldsymbol{x}_i)\prod\nolimits_{j=1}^{J}\prod\nolimits_{r_j=1}^{R_j}\rho_{j,r_j|c}^{I(y_j=r_j)} \tag{1}$$

where $\gamma_c(\boldsymbol{x}_i)$ is the prior probability of belonging to class c (considering a given response $\boldsymbol{x}_i$), with $c=1,\cdots,K$, and $\rho_{j,r_j|c}$ is the class-conditional probability of giving the response r_j to item j, given that the individual belongs to class c. The exponent $I\left(y_j=r_j\right)$ is an indicator function whose value is equal to 1 if the response to item y_j is r_j or 0, otherwise. The structure of Equation (2) indicates that the LCR model assumes local independence, i.e., conditional upon value of the latent variable, responses to all of the indicator variables are assumed to be statistically independent (Andersen et al., 2003). For the present case, $\boldsymbol{y}_i$ is a vector of 4 elements representing the response given by individuals to the frequencies of work trips and teleworking both before and during the pandemic, with alternatives (r_j) ranging from "Not Applicable/never/rarely" to "4 or more times a week".

The second part of the model corresponds to a logit link function from a generalized linear model known as the class-membership function. It indicates the effects of the covariates on the prior probability of an individual i of belonging to a class c^*. Then, considering $c=1$ as the reference class (Dayton et al., 1988):

$$\gamma_{c=c^*}(\boldsymbol{x}_i) = P(c = c^* | \boldsymbol{X}_i = \boldsymbol{x}_i) = \frac{\exp(\beta_{0c^*} + \beta_{1c^*}x_{1c^*} + \cdots + \beta_{pc^*}x_{pc^*})}{1 + \sum_{c=2}^{K}\exp(\beta_{0c} + \beta_{1c}x_{1c} + \cdots + \beta_{pc}x_{pc})} \quad (2)$$

where β_{qc} are the regression coefficients of a multinomial logistic regression, whereby $q = 0, \cdots, p$ represents the indices of the intercept and of the p covariates in the model. The solution involves an iterative estimation process of the prior (γ) and of the class-conditional (ρ) probabilities by maximum likelihood using the Expectation-Maximization (EM) algorithm (Dempster et al., 1977).

A diagramatic view of the proposed Latent Class Regression model, with its structural and measurement components can be seen in Fig. 4. The analysis was implemented with the poLCA package for the R programming language (Linzer and Lewis, 2014).

Since the number of classes (K) must be determined in advance, goodness-of-fit statistics are calculated for different values of K, with the Bayesian Information Criteria (BIC), which is a sound criterion for selection (Nylund et al., 2007; Schreiber, 2017). This is performed by running an LCA model (without covariates) for each value of K and choosing the one with the lower BIC statistic to be subsequently adjusted in the LCR model. However, interpretability also plays a role in this process, as "a class solution with superior statistics is not useful if it makes no sense theoretically" (Weller et al., 2020).

Due to the shape of the likelihood function, the convergence of the model depends on the set of starting values (Lanza et al., 2012). To overcome this issue, the LCR model was estimated 100 times to select the one with the highest value of the log likelihood for comparison. Metrics of absolute fit are also common for LCR, such as the likelihood-ratio chi-square statistic (G^2). Nonetheless, due to the many possible response patterns ($5^4 = 625$ combinations in $\boldsymbol{y}_i$), cell frequencies with few or no values are common and the chi-square statistic cannot approximate a chi-square distribution (Lanza et al., 2012). In that case, a direct comparison of the class-conditional probabilities predicted by the model with the observed frequencies of the response variables after assigning the classes to the individuals was carried out. A relative entropy statistic based on the posterior probabilities of the model was also calculated to assess the quality of class separation (Dziak et al., 2014). The relative entropy statistic measures how clearly or confidently a model classifies the subjects in terms of posterior probabilities, ranging from 0 to 1. Although there is no agreed cutoff value, the literature indicates that values closer to 1 are ideal and that a good separation are reached with values of 0.8 or above (Nylund-Gibson and Choi, 2018; Weller et al., 2020). A final diagnostic recommendation which was followed was to select only models with no class with less than 25 cases or 1% of the sample (Berlin et al., 2014).

3.3.3. *Changes in frequencies and travel mode choice for 2020 and 2021*

In this last step, the frequencies of work trips and teleworking as well as travel mode choice of the respondents in the three periods (t_0, t_1 and t_2) were analyzed. It is worth mentioning that the transitions were analyzed for the subset of observations that had their substitution patterns computed in the LCR analysis and were working at t_2 (which amounts to 144 individuals). The main flows between categories throughout these periods were identified with Sankey diagrams and discussed for each group of substitution patterns classified using the data from the first wave.

4. Results and Discussion

The survey of the first wave was completed by 702 respondents from 20 out of the 27 Brazilian states. As mentioned earlier, 524 valid respondents were selected, corresponding to those who were working in t_1 and were not unemployed, retired or on furlough in t_0. One year later, 192 individuals responded to the follow-up survey (second wave), from which 152 of them were working. Table 5 presents the statistical summary of sociodemographic attributes, travel behavior associated with work trips and teleworking habits.

In summary, the sample is constituted mainly of young and middle-aged adults (81.3%), marginally unbalanced toward female respondents (54%) and of highly educated individuals (roughly 86% have at least an undergraduate degree). According to the Brazilian Institute of Geography and Statistics (IBGE) estimates, young and middle-aged adults compose 62.9% of the Brazilian population, whereas females correspond to 51.8% and individuals with an undergraduate degree represent 17.3% of those over 25 years old (IBGE, 2019). It is worth mentioning that the overrepresentation of respondents with more years of education is quite common in this kind of research (Ben-Elia et al., 2014; van den Berg et al., 2013), including those carried out during the pandemic (Rahman Fatmi et al., 2022; Shakibaei et al., 2021). From the working perspective, at least 69% of the individuals were facing some sort of

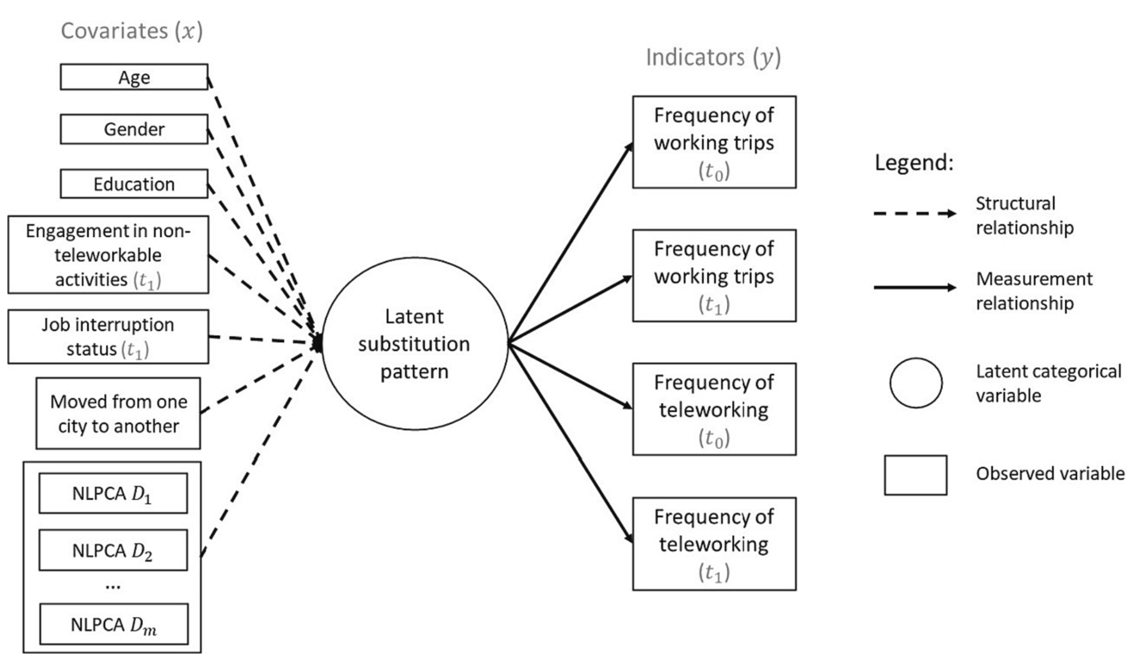

Fig. 4. Graphical representation of the Latent Class Regression model.

Table 5
Frequency distributions of the variables ($n_{w1} = 524$ and $n_{w2} = 152$).

Variable	Levels
Age	18–49 (81.3%), 50 or more (18.7%)
Gender	Female (54.0%), male (45.4%), other (0.4%), did not answer (0.2%)
Education	No degree (13.7%), undergraduate degree (32.8%), graduate degree (53.5%)
Moved to another city	No (91.6%), Yes (8.4%)
In-person job interruption status (t_1)	Not interrupted (30.9%), partially interrupted (27.9%), fully interrupted (41.2%)
Teleworkability of the Occupation (t_0)	Mean (0.8194), Median (0.8333), Std. Deviation (0.3491), Min (0), Max (1)
Teleworkability of the Occupation (t_1)	Mean (0.8189), Median (0.8250), Std. Deviation (0.3478), Min (0), Max (1)
Work trip frequency (t_0)*	F1 (6.3%), F2 (2.5%), F3 (2.5%), F4 (8.9%), F5 (79.8%)
Work trip frequency (t_1)*	F1 (47.5%), F2 (3.4%), F3 (4.8%), F4 (12.4%), F5 (31.9%)
Work trip frequency (t_2)*	F1 (35.5%), F2 (2.6%), F3 (9.9%), F4 (9.2%), F5 (42.8%)
Predominant mode of work trips (t_0)**	PT (19.7%), PC (57.4%), MO (4.8%), WK (7.3%), BC (1.3%), RS (5.3%), NA (4.2%)
Predominant mode of work trips (t_1)**	PT (7.3%), PC (56.1%), MO (3.4%), WK (5.7%), BC (1.0%), RS (6.1%), NA (20.4%)
Predominant mode of work trips (t_2)**	PT (13.2%), PC (52.6%), MO (2.0%), WK (7.9%), BC (1.3%), RS (7.2%), NA (15.8%)
Teleworking frequency (t_0)*	F1 (40.8%), F2 (5.3%), F3 (8.8%), F4 (16.8%), F5 (28.2%)
Teleworking frequency (t_1)*	F1 (12.2%), F2 (2.5%), F3 (3.4%), F4 (13.6%), F5 (68.3%)
Teleworking frequency (t_2)*	F1 (22.4%), F2 (3.3%), F3 (4.6%), F4 (15.8%), F5 (53.9%)

Legend: t_0 = early March 2020 (before the pandemic); t_1 = from 19th September to 18th October 2020; t_2 = from October 6 to November 5, 2021; n_{w1}, n_{w2} = sample size of working individuals in waves 1 and 2.
*Frequency of work trips: F1: Not applicable/rarely/never; F2: Less than 4 times a month; F3: Once a week; F4: 2 or 3 times a week; F5: 4 or more times a week.
**Mode choices: PT: public transit; PC: private car; MO: motorcycle; WK: walking; BC: bicycle/e-scooter; RS: ridesourcing; NA: not applicable.

disruption of in-person work activities, which can be noticed by the simultaneous declining of work trips and growth in teleworking from t_0 to t_1. Another important fact was the significant drop in public transit trips in the sample, probably associated with a higher risk perception linked to this mode. In the second wave (t_2), with a more controlled situation of the pandemic, a slight return to more work trips and less teleworking is more noticeable, but not sufficient to recover pre-pandemic figures. Likewise, there has been a recovery in public transit use, but still below the baseline figure.

4.1. Dimensions of physical and virtual accessibility

Most variables from groups “d” and “f” in Table 3 used in the NLPCA were originally measured for both t_0 and t_1. However, few changes were observed in the levels of these variables between t_0 and t_1. In fact, most individuals did not alter their answers, in which the worst case was that of Internet quality where 23.9% respondents marked a different alternative in t_1 with respect to that in t_0. Therefore, to avoid the occurrence of the same variable referring to both periods appearing in the same component and not adding any information, only the measurements for t_1 were considered.

Initially, $m = 7$ principal components were chosen to be retained in the dimensionality reduction. The stability of this solution was attested by evaluating the model with $m = 6$ and $m = 8$, which yielded 7 eigenvalues greater than 1 in both cases. The procedure retained 67.9% of variability with these 7 components, which individually contributed with 16.43%, 13.77%, 9.60%, 9.13%, 7.43%, 6.28% and 5.28% of the total variation, respectively. The NLPCA loadings between each variable and principal component can be seen in Table 6. Loadings with an absolute value greater than 0.4 were highlighted in bold and italics to allow for better identification of the patterns.

Considering the presence of cross-loadings among the principal components, PC4 and PC6 were eliminated for the second step of the method. Therefore, only the components’ scores from PC1, PC2, PC3, PC5 and PC7 were used as covariates along with the sociodemographic attributes in the LCR model. Additionally, principal components’ scores from PC1 and PC2 were multiplied by minus 1 for a more straightforward interpretation. In summary, the following interpretation can be drawn for each principal component used in the analysis:

- PC1: higher levels of Internet quality, ICT cognitive engagement and ICT proficiency (**cognitive virtual accessibility**)
- PC2: ease in traveling without a car for all trip purposes (**ease of traveling without a car**)
- PC3: lower levels of motorcycle and bicycle possession and better quality of sidewalks, bicycle lanes and street pavement in the neighborhood (**provision of transportation infrastructure in the neighborhood**)
- PC5: higher perception of COVID-19 infection in the travel mode used to work before the crisis and lower car ownership (**non-car owners with higher perceived risk of infection**)
- PC7: non-PC owners with high possession of smartphones and/or tablets (**virtual accessibility regarding device ownership**)

4.2. Substitution patterns of work trips by teleworking

Before adjusting the LCR model on the 524 responses of the first wave (including t_0 and t_1), the number of classes (K) was evaluated for K ranging from 1 to 8 classes on LCA models without covariates. As demonstrated in Table 7, according to the BIC statistic criterion, $K = 2$ is the most appropriate choice. Pre-examining the model parameters from the LCR with $K = 2$, a cluster with practically no substitution of work trips by teleworking and another cluster with a fairly amount of substitution were produced. However, $K = 3$ was chosen since this option unveils a partition of the substitution group into moderate and intense substitution, allowing for a more enriched analysis of the results. Moreover, the BIC difference between $K = 2$ and $K = 3$ was of only a modest increase of 0.8%.

The LCR model adjusted for $K = 3$ resulted in class-membership (prior) probabilities of $\gamma_{C1} = 0.176$, $\gamma_{C2} = 0.404$ and $\gamma_{C3} = 0.420$, where $C1$, $C2$ and $C3$ are the designated names of the classes. Following the classification given by the posterior probabilities, the number of individuals in each class are $n_{C1} = 88$, $n_{C2} = 213$ and $n_{C3} = 223$, which does not violate the recommendation of more than 25 cases (or more than 1% of the total sample) per class (Berlin et al., 2014). Additionally, the relative entropy value calculated for our model was of 0.836, which implies a good separation among classes.

The predicted class-conditional can be seen in Table 8, where values greater than 0.2 are highlighted in bold.

As mentioned earlier, the outcomes from Table 7 suggest the formation of 3 groups of individuals with distinct levels of substitution of work trips by teleworking. The first class ($C1$) presented the highest frequency of in-person work activities in both t_0 and t_1, with also lower frequencies of teleworking, indicating individuals with no or low

Table 6
Loading matrix from the principal components of the NLPCA.

Variable	PC1	PC2	PC3	PC4	PC5	PC6	PC7
Internet quality (t_1)	**−0.48**	0.11	0.04	0.18	−0.11	0.12	−0.40
Smartphone ownership (t_1)	−0.33	0.07	−0.05	0.02	0.02	0.19	**0.59**
Personal computer ownership (t_1)	−0.28	0.05	0.01	−0.06	−0.06	−0.28	**−0.57**
Tablet computer ownership (t_1)	−0.16	−0.08	−0.13	−0.17	−0.37	−0.21	**0.48**
TIC Cognitive Engagement #1 (t_1)	**−0.70**	0.15	−0.01	0.04	0.00	0.11	0.15
TIC Cognitive Engagement #2 (t_1)	**−0.69**	0.14	−0.08	0.13	−0.06	0.26	−0.09
TIC Cognitive Engagement #3 (t_1)	**−0.81**	0.17	−0.10	0.08	−0.03	0.22	−0.09
TIC Cognitive Engagement #4 (t_1)	**−0.60**	0.11	−0.06	0.00	0.06	0.15	0.16
TIC Cognitive Engagement #5 (t_1)	**−0.62**	0.12	−0.12	0.19	0.00	0.20	−0.04
TIC Proficiency #1 (t_1)	**−0.59**	0.08	0.02	−0.10	0.18	**−0.62**	0.04
TIC Proficiency #2 (t_1)	**−0.47**	0.16	−0.04	−0.08	0.18	**−0.68**	0.08
Perceived probability of infection of travel mode in t_0	0.04	0.07	0.05	0.18	**0.83**	−0.01	0.11
Car ownership (t_1)	−0.06	−0.06	−0.16	−0.10	**−0.80**	−0.13	0.02
Motorcycle ownership (t_1)	0.01	−0.05	**−0.70**	**−0.66**	0.19	0.15	−0.08
Bicycle ownership (t_1)	0.01	−0.05	**−0.70**	**−0.66**	0.19	0.15	−0.08
Walking time to nearest grocery (t_1)	−0.12	−0.22	−0.24	−0.18	−0.08	−0.27	−0.03
Ease of traveling to work without a car (t_1)	−0.23	**−0.97**	0.09	0.01	0.06	0.03	−0.01
Ease of shopping in-person without a car (t_1)	−0.23	**−0.97**	0.09	0.01	0.06	0.03	−0.01
Ease of eating out without a car (t_1)	−0.23	**−0.97**	0.09	0.01	0.06	0.03	−0.01
Quality of sidewalks in the neighborhood (t_1)	−0.17	0.10	**0.57**	**−0.59**	−0.03	0.13	−0.05
Quality of bicycle lanes in the neighborhood (t_1)	−0.10	0.09	**0.53**	**−0.51**	0.08	0.07	0.01
Quality of street pavement in the neighborhood (t_1)	−0.15	0.10	**0.60**	**−0.58**	−0.01	0.07	0.02
Eigenvalues	**3.61**	**3.03**	**2.11**	**2.01**	**1.63**	**1.38**	**1.16**

Legend: t_0 = early March 2020 (before the pandemic); t_1 = from 19th September to 18th October 2020.

Table 7
LCA statistics for different number of classes (K).

K	Log-Likelihood	Number of parameters	BIC
1	−2,295.09	16	4,690.36
2	−2,197.50	33	4,601.62
3	−2,160.67	50	4,634.41
4	−2,130.89	67	4,681.30
5	−2,111.05	84	4748.07
6	−2,094.05	101	4,821.91
7	−2,080.64	118	4,900.13
8	−2,067.43	135	4,980.16

substitution of work trips. Unlike $C1$, the second class ($C2$) presented a moderate level of substitution of work trips by teleworking at the same time transition. Finally, the third class ($C3$) presented the most intense substitution pattern of all three classes, with almost no in-person working and the highest level of teleworking at t_1. It is also worth mentioning that although $C3$ presented the higher level of working from home during the pandemic, $C2$ seems to be the class that did more teleworking before the outbreak.

After assigning the classes to each individual according to the posterior probabilities of the LCR model, the observed distributions of teleworking and work trip frequencies in Fig. 5 clearly supports that the model attained an adequate fit. Indeed, the frequency distributions of work trips and teleworking both in t_0 and t_1 for each class are very similar to the response pattern frequencies given by the class-conditional probabilities from Table 8.

Assessing the coefficients of the multinomial logit component of the LCR (Table 9), the contribution of work-related sociodemographic variables to the model is unequivocal. Indeed, the coefficients indicate that workers from $C2$ were more likely to be in partial interruption (hybrid regime) of in-person work activities during the pandemic than those from $C1$. Moreover, individuals from $C3$ did not only report more in-person job full interruption but were also more likely to be engaged only with teleworkable activities.

Observing the occupations appointed by individuals from each class (Fig. 6), one can see that activities associated with health and security professions, which predominantly require physical attendance, were more frequent for individuals in $C1$ than for those in $C2$ and $C3$. At the same time, $C3$ individuals were more engaged with activities such as researching and teaching, which are more feasible to be performed remotely. This outcome is in line with the results of previous research regarding the predominance of high-skilled workforce in occupations that are more amenable to teleworking (Dingel and Neiman, 2020; Góes

Table 8
Class-conditional ($\rho_{j,r_j|c}$) and class membership (γ_c) probabilities of the LCR model with..$K = 3$

		$C1$	$C2$	$C3$
Variable	**Levels**	γ_{C1} = 0.176	γ_{C2} = 0.404	γ_{C3} = 0.420
Work trips (t_0)	Not applicable/rarely/never	0.083	0.027	0.087
	Less than 4 times a month	0.023	0.036	0.015
	Once a week	0.000	0.018	0.038
	2 or 3 times a week	0.087	0.085	0.098
	4 times or more a week	**0.808**	**0.833**	**0.763**
Work trips (t_1)	Not applicable/rarely/never	0.127	0.178	**0.911**
	Less than 4 times a month	0.000	0.068	0.017
	Once a week	0.000	0.066	0.051
	2 or 3 times a week	0.181	**0.227**	0.000
	4 times or more a week	**0.692**	**0.470**	0.020
Teleworking (t_0)	Not applicable/rarely/never	**0.784**	**0.258**	**0.398**
	Less than 4 times a month	0.054	0.052	0.046
	Once a week	0.089	0.074	0.103
	2 or 3 times a week	0.073	**0.227**	0.156
	4 times or more a week	0.000	**0.389**	**0.297**
Teleworking (t_1)	Not applicable/rarely/never	**0.650**	0.013	0.000
	Less than 4 times a month	0.098	0.015	0.000
	Once a week	0.108	0.025	0.008
	2 or 3 times a week	0.127	**0.247**	0.036
	4 times or more a week	0.017	**0.700**	**0.956**

Legend: t_0 = early March 2020 (before the pandemic); t_1 = from 19th September to 18th October 2020.

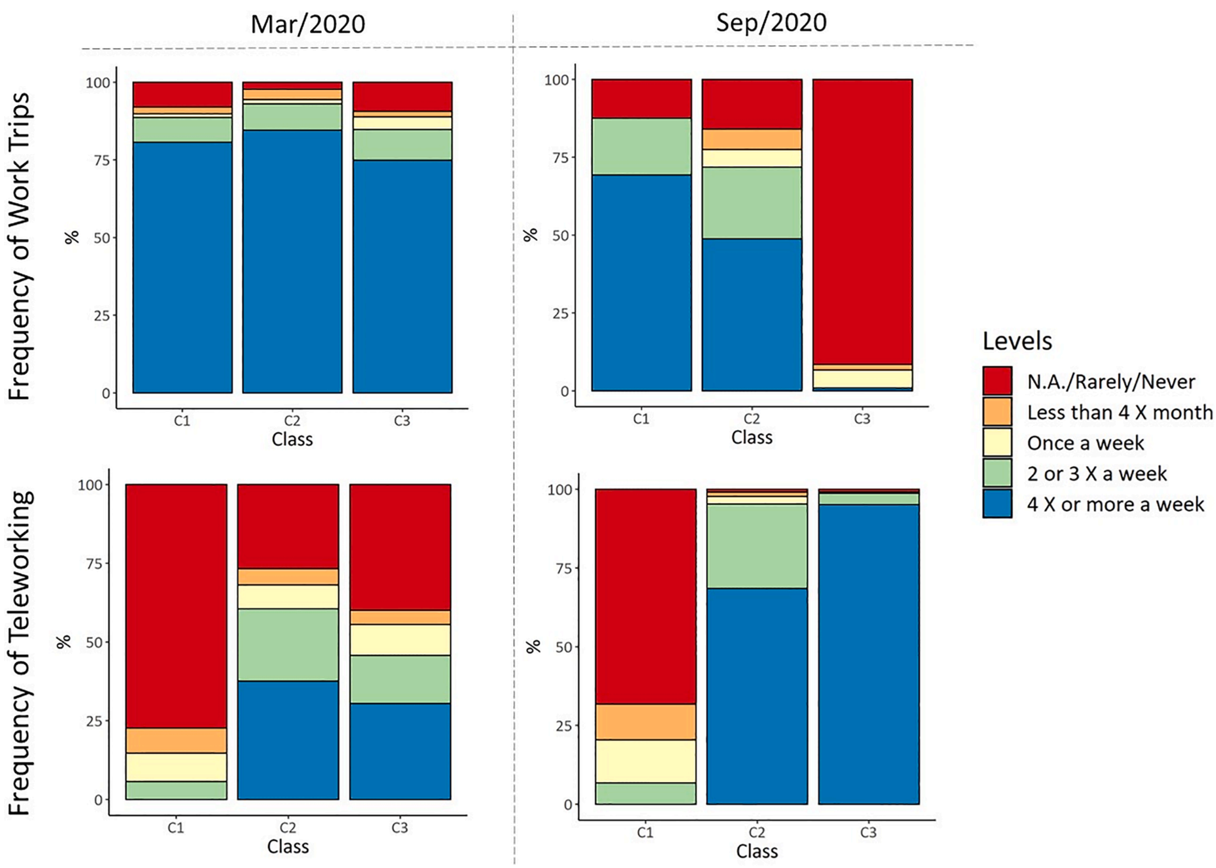

Fig. 5. Distribution of work trip frequency and teleworking frequency (for t_0 and t_1) per class.

et al., 2020).

With respect to sociodemographic variables, it was found that females are more predominant in class $C3$ when compared to $C1$. This finding is in line with some studies conducted during the pandemic that found a preference for teleworking among women (Hiselius and Arnfalk, 2021; Kroesen, 2022; Rahman Fatmi et al., 2022), which were also less likely to travel and engage in out-of-home activities (Fatmi et al., 2021; Irawan et al., 2021). The model also reveals a slight indication (at the 10% level) of a higher proportion of individuals aged between 18 and 49 years belonging to $C2$ when compared to $C1$ (although this result is not very informative given that we analyzed only two categories). This finding seems to contradict the positive correlation between age and teleworking frequency during the pandemic found in some studies, such as the US nationwide survey carried out by Salon et al. (2022). However, besides the fact that the latter analyzes the relationship with more detailed age categories (18–24, 25–34, 35–49, 50–64 and 65 +) there is also evidence in the literature that young and middle-aged individuals reduced more out-of-home activities (Fatmi et al., 2021). This contradiction sheds light on the necessity of investigating the frequencies of work trips and working from home jointly to have a clearer picture of the phenomenon. Moreover, a possible answer to having a higher proportion of young and middle-aged individuals in $C2$ can be attributed to the negative relationship between tech-savviness and age (probably not captured by the elements of ICT engagement in our model). Indeed, another pandemic study has pointed to young individuals who are more satisfied with virtual collaboration in the context of Swedish public agencies (Hiselius and Arnfalk, 2021).

Concerning the factors represented by the principal components, there is a strong indication that individuals from $C2$ and $C3$ are more cognitively engaged with ICT (PC1) and had more physical accessibility (PC2) than those in $C1$. For two reasons, this is the most remarkable finding of the present study. First, we show that even after accounting for the amenability of the job to telework, having positive attitudes towards ICT and being more proficient with these technologies strongly contributes to the substitution of work trips by teleworking. Since it may constitute an important factor in molding intentions to continue teleworking after the crisis, monitoring this aspect appears to be relevant. To the best of the authors' knowledge, no study has addressed the contribution of these factors so far. Second, individuals from $C2$ and $C3$ also seem to have higher physical access to opportunities, which indicates that they probably live in privileged urban areas and/or have adequate access to public transit. This positive correlation between physical and virtual accessibility might be due to the socioeconomic status of the individuals, which can be noticed from the distribution of occupations among the different classes (Fig. 6). Even though we did not measure the household income in our survey, it can be seen that those individuals from $C1$ are more likely to be employed in manual jobs than in occupations that are more amenable to telework and usually pay more. Additionally, a modest difference in device ownership (PC7) between classes $C2$ and $C1$ was also found, which can be directly observed from the data. Indeed, 98.4% of $C2$ individuals have a personal computer compared to only 84.1% of those in $C1$.

To allow for a comparison between classes $C2$ and $C3$, the model was readjusted with $C2$ as the reference class, whose results are summarized in Table 10 (only the coefficients of the equation comparing $C2$ and $C3$ were shown). The most prominent differences (with coefficients significant at the 5% level) refers to the form of in-person interruption, having moved to another city during the transition to the pandemic, the amenability of the job to telework and the individual's gender. Regarding the first two aspects, a larger proportion of individuals working in full in-person interruption of the job can be found in $C3$, whereas partial interruption was more predominant in $C2$. As expected, this situation might have enabled individuals from $C3$ to move from one city to another during the pandemic and prevented those in $C2$ from

Table 9
Multinomial logistic regression coefficients of the LCR model (reference level = *C*1).

Independent Variable	*C*2 β	Std. Error	*C*3 β	Std. Error
Intercept	−17.812	17.893	−45.290**	16.731
Age (*ref. = 18–49 years old*)				
50 years or more	−1.194^{+}	0.609	−0.620	0.610
Gender (*ref. = Female*)				
Male	−0.010	0.394	−1.121*	0.534
Education (*ref. = No degree*)				
Undergraduate	−0.313	0.516	1.131	0.814
Graduate	0.860	0.538	1.288	0.831
Moved from one city to another (*ref. = No*)				
Yes	0.391	1.215	2.169	1.124
In-person job interruption in the pandemic (*ref. = None*)				
Partial (hybrid regime)	1.689**	0.495	−0.062	0.810
Full	0.823	0.803	4.140***	0.827
Teleworkability of the occupation	0.825^{+}	0.463	5.889**	2.052
PC1 (cognitive virtual accessibility)	2.711*	1.086	3.082**	1.060
PC2 (ease of traveling without a car)	8.565*	4.330	8.124^{+}	4.153
PC3 (transportation infrastructure in the neighborhood)	−0.353	0.622	0.724	0.505
PC5 (non-car owners with high perceived risk of COVID-19 infection when traveling)	0.361	0.294	0.272	0.375
PC7 (device ownership)	−0.396^{+}	0.208	0.127	0.262

Significance coding: $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, ***.$p < 0.001$

Table 10
Multinomial logistic regression coefficients of the LCR model (reference level = *C*2)[1].

Independent Variable	*C*3 β	Std. Error
Intercept	−27.478*	12.604
Age (*ref. = 18–49 years old*)		
50 years or more	0.574	0.577
Gender (*ref. = Female*)		
Male	−1.110*	0.523
Education (*ref. = No degree*)		
Undergraduate	1.444^{+}	0.809
Graduate	0.428	0.788
Moved from one city to another (*ref. = No*)		
Yes	1.778*	0.780
In-person job interruption in the pandemic (*ref. = None*)		
Partial (hybrid regime)	−1.751*	0.745
Full	3.317***	0.634
Teleworkability of the occupation	5.064*	2.049
PC1 (cognitive virtual accessibility)	−0.371	0.603
PC2 (ease of traveling without a car)	−0.441	2.341
PC3 (transportation infrastructure in the neighborhood)	1.078^{+}	0.554
PC5 (non-car owners with high perceived risk of COVID-19 infection when traveling)	−0.089	0.330
PC7 (device ownership)	0.523^{+}	0.290

[1]Coefficients of the equation comparing *C*1 to *C*2 were not shown as this comparison is contemplated in Table 9.
Significance coding: $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, ***.$p < 0.001$

doing so. After considering these factors, *C*3 still presents higher levels of individuals engaged in more teleworkable occupations. Finally, the higher proportion of women seen in *C*3 when compared to *C*1 in Table 9 was also found in the comparison with *C*2, which reinforces the argument made earlier about the preference to work fully from home with the suspension of day care centers and primary schools and/or the higher risk perception of performing out-of-home activities.

More subtle differences (significant at the 10% level) were verified with respect to the education level, the quality of transportation infrastructure in the neighborhood and device ownership. In summary, the concentration of individuals with no degree is slightly higher in *C*2, and those in *C*3 have usually better access to higher quality roads, sidewalks and ICT devices. In summary, these findings indicate that differences in virtual and physical accessibility can also be manifested even when comparing moderate to intense substitution groups.

Finally, a statistical summary of the main characteristics of each latent class with respect to the significant variables from the multino-

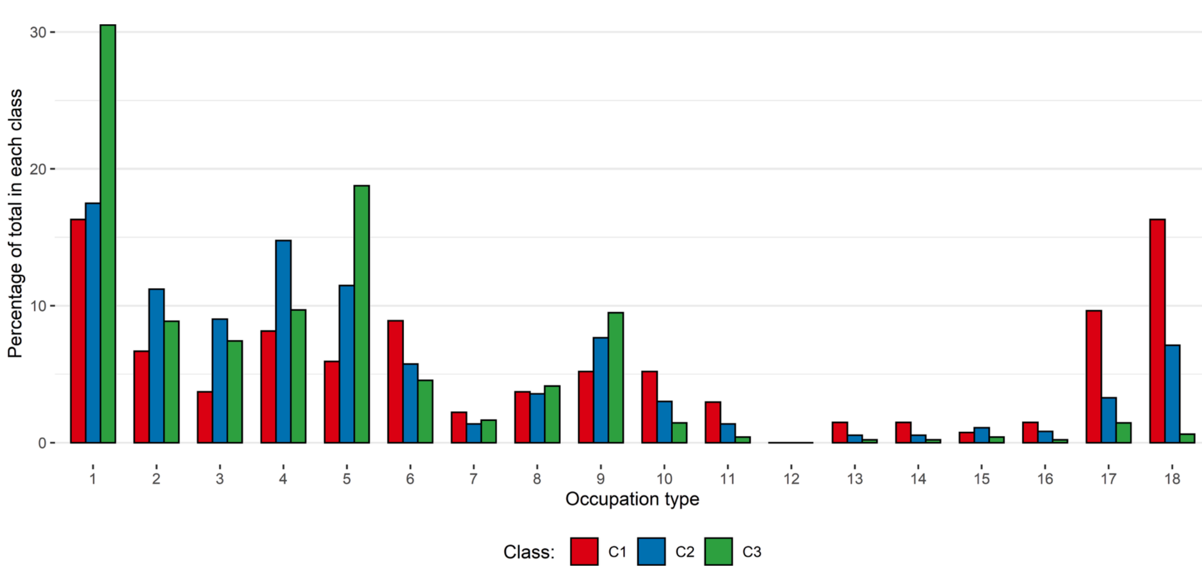

Fig. 6. Relative frequency of occupations appearing in each class of the LCR Legend: 1 - Research, analyze, evaluate, develop; 2 - Design, plan, sketch; 3 - Execute or interpret laws/rules; 4 - Employ or manage personnel, lobby, organize, coordinate; 5 – Teach; 6 - Sell, buy, advise clients, advertise; 7 - Publish, present, entertain others; 8 - Calculate, do bookkeeping, control financial resources; 9 - Correct text or data, program, register information, organize documents; 10 - Measure, quality control, perform laboratory tests; 11 - Equip or operate machines; 12 – Repair, renovate, reconstruct; 13 – Cultivate; 14 - Manufacture, install, construct, mold materials, cook, build; 15 – Cleaning; 16 - Pack, ship or transport products; 17 - Serve, accommodate, nurse or treat others; 18 – Secure.

Table 11
Statistical summary of the significant variables of the multinomial logit model for each latent class.

Variable	Level/Descriptive Statistic	$C1$	$C2$	$C3$
Age	18–49	80.5%	88.4%	77.4%
	50 or more	19.5%	11.6%	22.6%
Gender	Female	51.7%	51.4%	57.5%
	Male	48.3%	48.6%	42.5%
Education	No degree	28.7%	14.9%	7.9%
	Undergraduate degree	39.1%	33.1%	31.2%
	Graduate degree	32.2%	51.9%	61.9%
Moved to another city	No	97.7%	93.9%	86.5%
	Yes	2.3%	6.1%	13.5%
In-person job interruption status	Not interrupted	70.1%	37.6%	13.1%
	Partially interrupted	21.8%	50.8%	12.7%
	Fully interrupted	8.1%	11.6%	74.2%
Teleworkability of the Occupation	Mean	0.516	0.793	0.942
	Std. Deviation	0.457	0.351	0.206
PC1 (cognitive virtual accessibility)	Mean	−0.667	0.136	0.131
	Std. Deviation	1.400	0.820	0.777
PC2 (ease of traveling without a car)	Mean	−0.075	0.084	0.061
	Std. Deviation	0.227	0.385	1.660
PC3 (transportation infrastructure in the neighborhood)	Mean	0.157	−0.090	0.076
	Std. Deviation	0.741	0.494	0.822
PC7 (device ownership)	Mean	0.209	−0.176	0.051
	Std. Deviation	1.400	0.847	0.909

mial logit model is presented in Table 11. Accordingly, the main features of each latent class can be summarized as follows:

- $C1$: individuals with the lowest education level among all classes, who mostly did not have their in-person work interrupted given the limited amenability to telework of their occupations. They are also less cognitively engaged with ICT and are less likely to own a personal computer than the other groups.
- $C2$: together with $C3$, these are the individuals with the highest education levels among all classes, mostly engaged in partial remote work and occupied in teleworkable occupations. They are also more cognitively engaged with ICTs, find it easier to travel without a car, and almost all individuals own a personal computer.
- $C3$: mostly individuals with a graduate degree, in which the highest proportion of women are engaged in full remote work. These individuals are employed in occupations with the highest level of teleworkability among all classes, which has allowed part of them to move to another city during the pandemic. They are also very cognitively engaged with ICT and have a high level of personal computer ownership."

4.3. Changes in work trips, teleworking and travel mode choice from 2020 to 2021

To monitor activity-travel behavior of the individuals in each group, the frequencies of work trips, teleworking and mode choices in t_2 (October 6 to November 5, 2021) were compared to the previous periods, t_0 (early March 2020, before the pandemic) and t_1 (September 19 to October 18, 2020). In the second wave of data, 192 valid answers were obtained, from which 152 consisted of individuals who were working at t_2. Nevertheless, considering specifically the 524 individuals who have been used to adjusting the LCR model, this number slightly reduces to 144 answers. From these, 25 individuals were categorized as $C1$, 39 as $C2$ and 80 as $C3$ in the previous wave, which are chosen to be monitored in the current stage of the methodological procedure.

Figs. 7 and 8 show the variation in the frequency of work trips and teleworking, respectively, using Sankey diagrams for these 144 observations. From a visual inspection, it can be seen that those individuals in

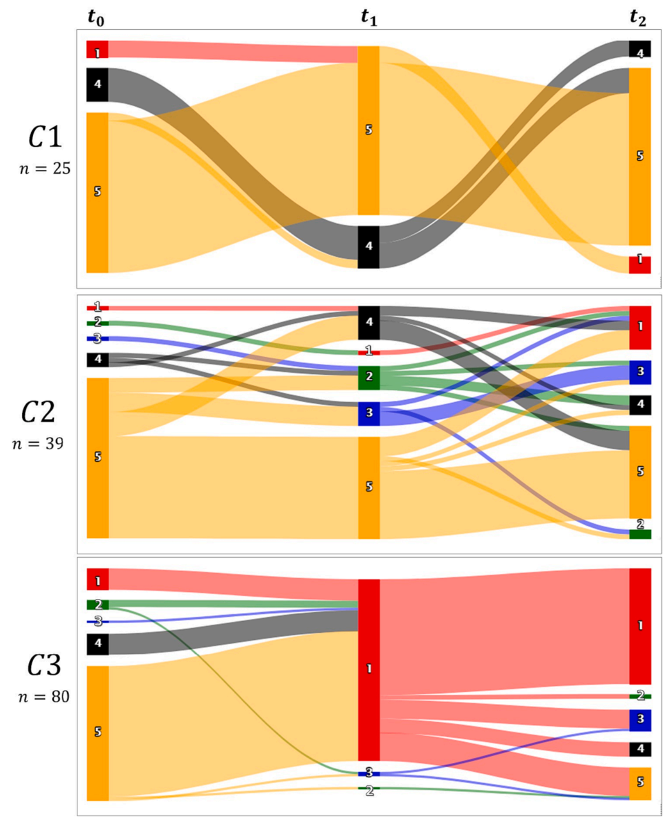

Fig. 7. Change in frequency of work trips in the three analyzed periods for each substitution class Legend: Frequency of work trips: 1: Not applicable/rarely/never; 2: Less than 4 times a month; 3: Once a week; 4: 2 or 3 times a week; 5: 4 or more times a week; t_0 = early March 2020 (before the pandemic); t_1 = September 19 to October 18, 2020; t_2: October 6 to November 5, 2021; $C1$: no/low substitution class; $C2$: moderate substitution class; $C3$: intense substitution class.

$C1$ continued to travel with high frequency in t_2, in which some of them diminished the low level of teleworking gained in t_1. Regarding $C2$, both transitions of increase (12) and of decrease (9) in work trips from t_1 to t_2 can be noticed. Furthermore, a reduction in teleworking frequency for individuals in C2 was also found, indicating a return to in-person work in t_2 for some of these individuals. It is worth mentioning that this level of teleworking in t_2 is very similar to that in t_0, indicating a return to the pre-pandemic pattern in this group. For those in $C3$, an increase in the number of trips in parallel to a slight reduction in teleworking is observed from t_1 to t_2. However, unlike $C2$, this group is far from returning to the pre-crisis work trips and teleworking frequencies baseline, which is probably due to the higher amenability of their jobs to teleworking.

With respect to the travel mode choice transitions (Fig. 9), one of the most prominent features is the increase in car passenger trips from t_0 to t_1 for these groups of individuals who continued to travel to work ($C1$ and $C2$). This can be largely attributed to the relatively higher protection against contagion offered by this travel mode with respect to its counterparts. With respect to the $C3$ group, the major transitions observed due to the pandemic (from t_0 to t_1) are related to the overall reduction in mobility. However, the reduction in private vehicle use was only of 20% (40 to 32 individuals), whereas public transit use shrunk almost 90% (from 26 to 3 individuals). One year later (t_2), in a more controlled scenario, the number of public transit users in this group was less than half of that it was before (11), while car users returned back to pretty much the same of the volume in t_0 (39). It should be noted, though, that from the initial 26 public transit users (t_0), 15 moved to no travel at all (t_1), a particular trend that has been observed in previous work

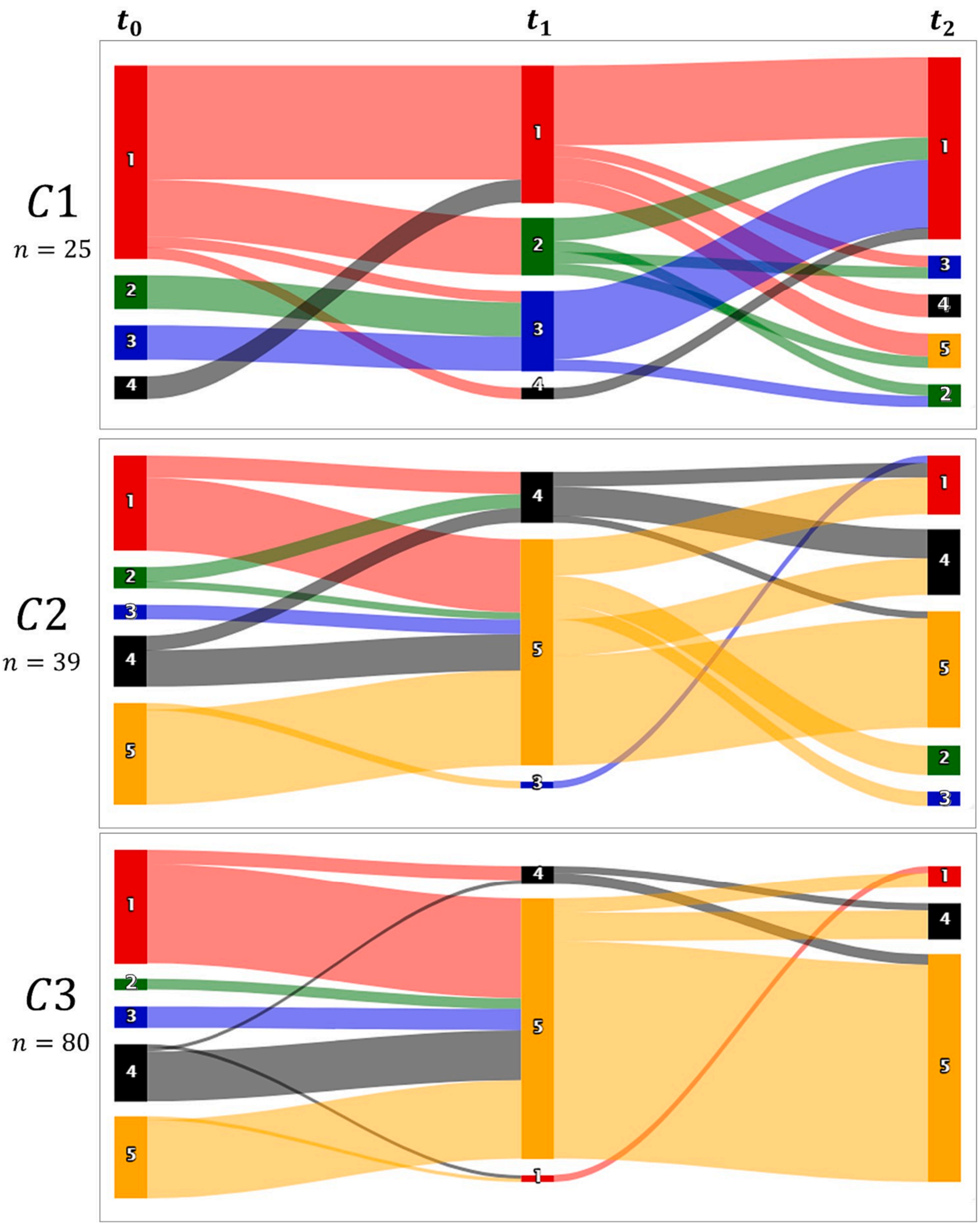

Fig. 8. Change in frequency of teleworking in the three analyzed periods for each substitution class Legend: Frequency of work trips: 1: Not applicable/rarely/never; 2: Less than 4 times a month; 3: Once a week; 4: 2 or 3 times a week; 5: 4 or more times a week; t_0 = early March 2020 (before the pandemic); t_1 = September 19 to October 18, 2020; t_2: October 6 to November 5, 2021; $C1$: no/low substitution class; $C2$: moderate substitution class; $C3$: intense substitution class.

(Shibayama et al., 2021). The greatest concern in this case is whether in the near future these individuals will continue to telework and, if not, which travel mode they will be choosing to travel on.

5. Conclusions

This research assessed the emergence and endurance of substitution patterns in work trips due to teleworking for the first two years of the COVID-19 pandemic in Brazil using a longitudinal survey. First, we were able to distinguish three patterns within the sample, namely: no/low substitution, moderate substitution (hybrid/partial remote work) and intense substitution (full remote work). Addressing the phenomenon with that kind of granularity is still a limitation of the literature of travel behavior and teleworking during the COVID-19 crisis. The results also endorsed previous studies indicating that substitution is highly associated with high-skilled occupations that typically pay more than manual jobs. Indeed, the amenability of the occupation to telework was the main aspect that supported the distinction between groups, which was positively correlated with the amount of in-person work substitution by telework. Moreover, we found that women were more likely to telework, which can be probably credited to their more precautionary behavior when compared to male individuals (Borkowski et al., 2021). It is also possible that traditional gender roles associated with childcare have contributed to less out–of–home activities due to the long period of closures in day care centers and primary schools (Bohman et al., 2021; Rodrigues da Silva et al., 2023). We also found that those working fully from home are also more educated than those who did not telework and had a higher likelihood of moving to another city during the pandemic

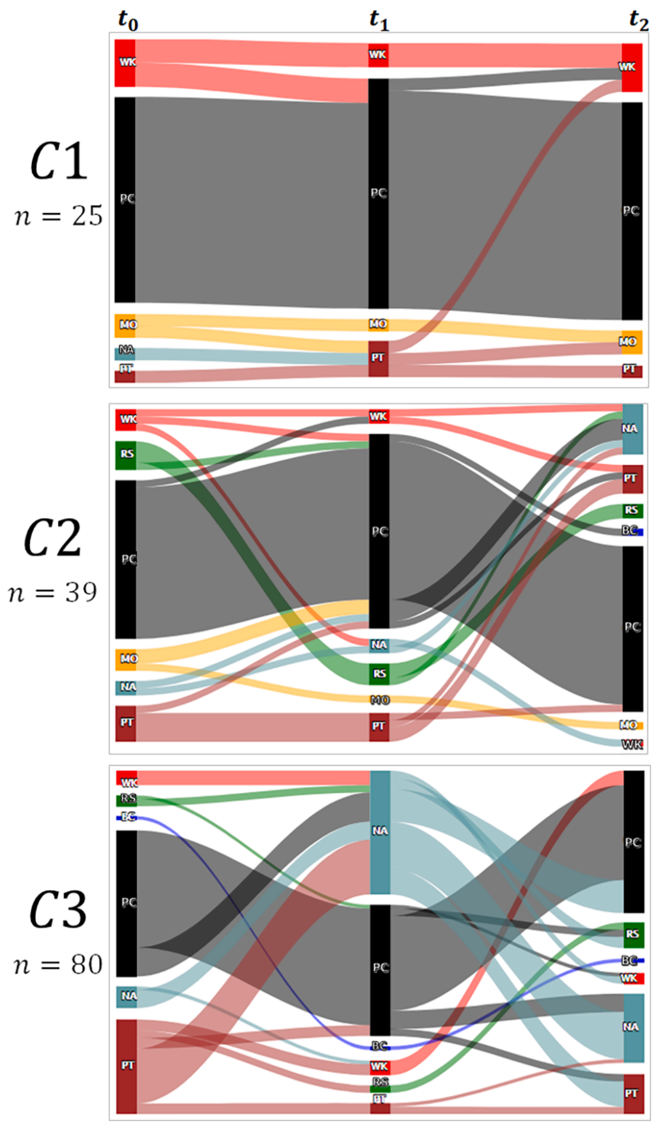

Fig. 9. Changes in travel mode choice in the three analyzed periods for each substitution class Legend: mode choices: WK: walking; RS: ridesourcing; BC: bicycle/e-scooter; PC: private car; MO: motorcycle; PT: public transit; NA: not applicable; t_0 = early March 2020 (before the pandemic); t_1 = September 19 to October 18, 2020; t_2: October 6 to November 5, 2021; $C1$: no/low substitution class; $C2$: moderate substitution class; $C3$: intense substitution class.

than those who did partial remote work (probably related to the flexibility of this kind of work regime).

Another contribution was to unveil relationships of substitution patterns with important (but usually overlooked) dimensions of virtual accessibility, such as cognitive engagement with ICT and the ability to use technological tools. Particularly, we found that those individuals who worked fully or partially from home usually present more positive attitudes toward ICT than those who did not. This is an indication that with the acceleration of activities and services migrating to the virtual environment, the so-called “digital apartheid” or “digital divide” (Scheerder et al., 2017) will add to the existing inequality in physical access to urban amenities and services. Although this problem might not appear to be relevant in developed economies, one in five Brazilian households lacks access to the Internet and only in half of them one can find a personal computer (Rodrigues da Silva et al., 2023). Unsurprisingly, these low-income households are also predominantly located in urban areas with lower physical accessibility (Pereira et al., 2022). Similar trends were also discussed in other studies during the pandemic (Bohman et al., 2021; Irawan et al., 2021; Shamshiripour et al., 2020).

It was also found that individuals who did not replace physical work by teleworking or did it moderately in 2020 were more likely to return to pre-pandemic habits in 2021 than those who replaced it intensively. This finding indicates that the persistence of teleworking in a post-pandemic era might occur more prominently in those occupations fully amenable to remote work. Finally, our data endorses worldwide concerns about the drop in public transit ridership induced by the COVID-19 pandemic, which was mainly diverted to the private car or remote working.

These findings draw attention to the design and implementation of important policies in a post-pandemic scenario. Notably, universalizing ICT device use and expanding Internet coverage (and quality) are important, but not sufficient, as inclusion will be only effective for people who are also proficient enough to competently use gadgets and their functionalities. As revealed in previous studies, these differences exist not only across socioeconomic groups, but also among age groups, as older individuals tend to be less tech-savvy than younger ones. This fact must not be ignored in a quickly ageing world. Accordingly, educational policies directed toward increasing digital literacy play a crucial role in mitigating these inequalities.

Equally important is devising tailored policies for specific groups that continued to telework even after the attenuation of the crisis. Considering a scenario wherein teleworking loses momentum and people gradually return to in-person work, there is a matter of concern about their future mode choices. Our analysis raises an alert regarding this topic as some individuals in the group that replaced all work trips by teleworking returned to private cars more than to public transit in the last quarter of 2021. Active modes and especially public transit (which is undergoing a critical demand problem in Brazil accentuated by the COVID-19 pandemic) must be prioritized in the public budget so as to increase their relative attractiveness with respect to private transport. Given that this group is also the one whose individuals are more cognitively engaged with ICT, investing in Information Technology (IT) solutions for public transit might constitute promising interventions. This includes, but is not limited to, real time information systems, Mobility-as-a-Service (MaaS) applications and improvements in payment technology (e.g., allowing for alternatives such as contactless cards or mobile devices).

Also relevant is monitoring housing choices these individuals are making after an extended period of teleworking. As identified in our data, more people in this group were able to move from one city to another during the pandemic, but it might also have been the case that the possibility of working remotely have led them to seek better (and/or cheaper) living opportunities in distant and low–density neighborhoods. This second order effect may worsen the existing problem of urban sprawling in developing countries that generate more unnecessary and longer trips in cities. Therefore, depending on the level of teleworking experienced in each region, future debates about land-use regulations must take this topic seriously into consideration. A first policy recommendation in this case is that local and regional authorities should conduct more comprehensive surveys to assess whether the magnitude of this impact is relevant. If that is the case, policies related to allowing for more mixed land use (to avoid the generation of excessive non-mandatory trips) and/or incentivizing the densification of neighborhoods (or discouraging low density expansion) should be considered.

The main limitation of our study is the sampling procedure which does not allow for the conclusions to be drawn to the whole Brazilian population. However, the proposed longitudinal design still allowed us to find important within-individual and distinct group patterns in a developing country. The study did not also measure important sociodemographic attributes, such as race and household income, which could help us to better characterize the differences in the groups found. This was mainly due to the challenge of balancing the scope of the questionnaire with favoring higher response rates as the first wave of collection required that individuals answered aspects about their behavior for two time points.

Moreover, although the last wave of collection represented a period of milder sanitary impacts, with almost half of the population vaccinated with the 2nd dose and low mortality rates, it does not represent a stage of complete elimination of sanitary concerns. Therefore, it is still a transition phase to a "new normal" scenario that most researchers are most willing to be compared with the pre-pandemic baseline. Conducting additional waves of the present research will add important information to the analytical process, covering a period of higher immunization rates and reopening of activities that will raise fundamental questions to be answered. These include the resilience of substitution work regimes, the recovery of public transit ridership and how virtual and physical accessibility might be associated with them. Analyzing these data longitudinally for an extended period will enable the identification of potential emerging urban lifestyles and their associated challenges and opportunities. This information will be crucial to refine and re-evaluate the policy recommendations stated before.

CRediT authorship contribution statement

Jorge Ubirajara Pedreira Junior: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Resources, Software, Visualization, Writing – original draft. **Cira Souza Pitombo:** Conceptualization, Formal analysis, Funding acquisition, Methodology, Project administration, Resources, Supervision, Validation, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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