Working from Home during the Pandemic: Analyzing Activity Patterns in the 2021 Post-vaccine Period

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Abstract

The ongoing health crisis of the COVID-19 pandemic and the imposed social distancing measures have led a significant portion of workers to adopt “working from home” arrangements, which have greater impacts on workers’ daily activity-travel routines. This new-normal arrangement will possibly be sustained in large measure since the pandemic returns at a certain interval with its new variants. This study explores the activity patterns of workers exclusively working from home (telecommuters) after the initial 2020 pandemic year and deemed as “the 2021 post-vaccine” year. We hypothesized that heterogeneous groups of activity *patterns* (daily sequence of activities and travel) exist among telecommuters. We classified the activity patterns of telecommuters via Latent Class Analysis. Our model results suggest that telecommuters’ activity patterns can be split into three distinct classes where each class is associated with several socio-demographics. Class 1 constituted workers from high-income households who tend to have a conventional work schedule but make non-work activities mostly in the evening. Class 2 was composed of workers from low to medium income, non-Asian households whose work is not pre-dominate but with out of home non-work activities spread throughout the day. Last, Class 3 members are workers of middle to older age, living without children, who primarily remain at home during the day with a conventional work schedule. If telecommuting is to continue at levels much greater than prior to the pandemic, then research insights regarding the variations of activity-travel demands of telecommuters could help to make telecommuting a successful travel demand management tool.

Keywords: Working from home, telecommuters, activity patterns, COVID-19 pandemic, Latent Class Analysis, 2021 ATUS

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Introduction

The nature of activity-travel patterns in 2019 drastically changed in 2020 due to the worldwide outbreak of the COVID-19 pandemic which introduced extreme disruption in daily routines, massive changes in activity-travel behavior, and millions of deaths worldwide. Due to public health concerns and imposed social distancing measures, teleworking, also known as “working from home” (WFH), emerged as a “new normal” arrangement for a significant portion of workers, a trend that has been sustained in large measure as the pandemic has cycled through transitional waves of viral variants. The year 2021 began with the introduction of COVID-19 vaccines which provided the first real opportunity to have prior behaviors re-established. Research is needed to examine if and when prior behavioral patterns re-emerge, particularly as new COVID-19 variants appeared.

Working from home has long been advocated as an effective travel demand management strategy as well as an environmental management tool for reducing travel and greenhouse gas emissions. The COVID-19 pandemic and the associated activity-travel restrictions imposed, despite creating immense disruption to our lives, have offered a unique opportunity to experience the ramifications of telework policies and practices on travel. Considering the widespread adoption of teleworking arrangements throughout the world, it appears that the post-pandemic workplace experience may be quite different than in the pre-pandemic era with employers more accommodating of work-from-home practices and other changes in work and non-work activity-travel arrangements. In this context, it is important to investigate the daily activity-travel patterns of workers working from home to understand their daily travel needs. Here, the term *pattern* refers to a complete sequence of activities (in-home and out-home) and trips made by an individual over a full day.

Recent research conducted during the pandemic has examined the rise of the work from home phenomena, changes in work productivity associated with new work arrangements, and prospects for the future. Brynjolfsson et al. (2020) found that between February and May 2020, over one-third of the American labor force replaced in-person work with working from home, which increased the share of remote working to nearly 50 percent of the nation’s workforce. Barrero et al. (2020) reported that one-third of total time savings in the U.S. due to not commuting to workplaces was allocated to the primary job and the rest was spent in leisure and household activities including childcare. Based on primary survey data, Beck and Hensher (2020) found in Australia that work from home was a positive experience among individuals and its practice might continue after the pandemic is over. Rafiq and McNally (2022c) investigated the impacts of working from home on travel. The changes in working from home and travel were also observed across different population geographies of the US in Rafiq and McNally (2022d). While the activity patterns of telecommuters were not considered in the recent pandemic studies, only a few pre-pandemic studies considered so (e.g., Su et al., 2021).

If telecommuting is to continue at or near pandemic levels, it is important to examine the level of behavior reflected in the activity-travel patterns of people working from home (telecommuters) during the pandemic. In this context, the major research question to address is whether heterogeneous groups of activity-travel patterns exist among people who work from home. The 2021 American Time Use Survey (ATUS) provides a unique opportunity to analyze the heterogeneity in the activity patterns of telecommuters during the 2021 post-vaccine period. This analysis will allow for the identification of variation in activity-travel patterns as well as the corresponding telecommuter classes who performed those patterns. These findings can help policy makers and planners to formulate strategies that can work better with WFH-policies to improve their success as travel demand management and environmental management tools.

Data and Summary Statistics

2.1 Dataset and Study Timeframe

This study uses data from the 2021 American Time Use Survey (ATUS), an annual survey conducted by the U.S. Census Bureau and sponsored by the Bureau of Labor Statistics (U.S. Bureau of Labor Statistics, 2021). This dataset provides nationally representative estimates of how, where, and with whom Americans spent their time for various activity-travel purposes including personal care, household activities, work, consumer purchase, socializing, eating, travel, and other activities. ATUS randomly selected households from the Current Population Survey and collects time-use and demographic information for one household member (aged 15 years and above) for one pre-assigned day (1440 minutes).

The year 2020 was a remarkably distinct year due to the global outbreak of the COVID-19 pandemic that has resulted in millions of deaths worldwide and drastic changes in day-to-day life. While the primary news focus throughout 2020 was how the pandemic was spreading in the world, in 2021 news was dominated by the development and distribution of vaccines to address the pandemic (AJMC, 2021). In this context, the 2021 ATUS data provided a unique opportunity to investigate how people adjusted their activity-travel behavior during the post-vaccine period. The total number of respondents in the 2021 ATUS data was 9,087. Details for the ATUS survey methodology, questionnaire, and data are available at https://www.bls.gov/tus/home.htm.

For this study, to capture the “working from home” phenomena, we considered those individuals who worked at home and did not make any commute trips on the diary day. We called these workers *telecommuters* throughout the paper. This generated a sample of 1,017 workers, where 673 persons denoted activities during weekdays and 344 reported activities during weekends. Since it is a single-day diary data, the criteria used for selecting telecommuters may not necessarily reflect an individual’s regular activity-travel behavior. Nonetheless, this selection will represent the generic activity patterns of telecommuters who worked at home during the survey day and made trips (if any) for various purposes other than work.

2.2 Summary Statistics

Throughout the ongoing COVID-19 pandemic, changes in daily activity-travel routines and time-use behavior, including the widespread adoption of telecommuting, have been manifold. Who did telecommuting during COVID? With regard to the socio-demographic characteristics of telecommuters, by using the 2020 ATUS data, Rafiq and McNally (2022b) shows that telecommuters were more likely to be married and belonged to dual-earner households. In addition, a higher proportion of telecommuters were from White and Asian households. Telecommuters mostly corresponded to high-income households. Similar findings was reported in McNally et al. (2022) and Beck and Hensher (2020).

In terms of person-level characteristics, a higher percentage of workers aged 36 – 45 were telecommuters compared to commuters, indicating that older workers tend to have greater flexibility in choosing work from home options. A similar finding was reported in Su et al.

(2021). The telecommuter group consisted of a higher percentage of female workers while the commuter group reflected a considerable portion of male workers. Beck and Hensher (2020) and Brynjolfsson et al. (2020) reported similar findings regarding gender during the pandemic. A higher education level had a positive association with telecommuting. McNally et al. (2022) found similar findings for the pre-pandemic period.

Did activity-travel behavior of telecommuters change due to the pandemic? We made comparisons of various activity-travel indicators of telecommuters among the year 2019, 2020, and 2021 by using the ATUS multi-year data. These three years were considered as the pre-, during-, and post-pandemic periods. Here, post-pandemic denotes the post-vaccine period. To estimate the statistical significance of differences, we conducted two *nonparametric* tests: (a) chi-square tests for categorical variables, and (b) Kruskal-Wallis (KW) tests for continuous and count variables. The results are shown in Table 1.

Table 1: Activity behavior of telecommuters in pre-, during, and post-pandemic periods

Variables	**2019** N = 606 (a)	**2020** N = 950 (b)	**2021** N = 1,017 (c)
Percentage of telecommuters by the number of trips			
# trips = 0	22.5^{bc}	48.7^{a}	42.7^{a}
# trips 1 – 2	26.8	24.8	24.9
# trips > 2	50.6^{bc}	26.4^{a}	32.4^{a}
Average number of trips per day	3.26^{bc}	1.77^{ac}	2.08^{ab}
Average travel time budget (in min)	57.8^{bc}	27.9^{ac}	32.0^{ab}
Average out-home non-work duration (in min)	129.8^{bc}	68.5^{ac}	72.8^{ab}
Average at-home work duration (in min)	283.0^{bc}	383.9^{a}	409.6^{a}
Longest work duration (in min)	180.8^{bc}	229.1^{a}	250.0^{a}
Total at-home activity duration	1253.4^{bc}	1344.2^{ac}	1336.4^{ab}

Note: The table shows mean values for all variables. Mean values for binary variables are shown in percentages. All the binary variables (except for number of trips 1 – 2) and continuous/count variables were jointly significant at a 5% significance level in chi-square and Kruskal-Wallis (KW) tests, respectively. Superscripts a, b, and c indicate that values were significantly different (at 5% significance level) from activity participation values for pre-(2019), during (2020), and post-pandemic (2021) periods, respectively, in post-hoc tests.

Table 1 shows the summary statistics of the number of trips, the average time spent on work, non-work, and travel, and the average dwelling time at home of telecommuters in these three years. It is observed that telecommuters stayed more time at home during- and post-pandemic years (2020 and 2021) than in the pre-pandemic year (2019), and that they spent less time for out-of-home non-work activities and travel in 2020 and 2021 compared to 2019 (all these differences are statistically significant with 5% level of significance). In 2019, telecommuters worked about 283 minutes in a day at home, whereas in the years 2020 and 2021, they worked considerably higher amounts of time at home (383 minutes and 409 minutes, respectively). The trip counts of telecommuters also varied in these three years: in the years 2020 and 2021, around 48 and 42 percent of telecommuters did not make any trip in a day (trip count was zero), whereas in 2019 this fraction was only 22 percent. During the pandemic (in 2020), the average number of trips per day was 1.77, whereas in 2019 and 2021, this number was much higher: 3.26 and 2.08 trips per day, respectively.

Methodology

In this study, we analyzed the heterogeneity in activity-travel patterns of telecommuters during 2021, the first post-vaccine period of the pandemic. Here, we use the term *pattern* to refer to an entire day's agenda represented as a 24-hour sequence of in-home and out-of-home activities and travel as a focus to better understand the travel behavior of telecommuters.

We captured the heterogeneity of activity-travel patterns of telecommuters by segmenting workers into a set of sub-groups with representative activity patterns using Latent Class Analysis (LCA). LCA has been used in a range of travel behavior research where the heterogeneity in target groups is observed in terms of individual demographics, lifestyles, attitudes, preferences, neighborhood characteristics, and travel behavior indicators. For example, Beckman and Goulias (2008) classified immigrants based on travel time, mode choice, and departure time for work. Similarly, millennials were divided based on their commute and non-commute mode choice in Lee at al. (2019). Davis et al. (2018) classified the non-commute long-distance travelers based on travel distance, trip purpose, and tour duration. In addition to travel behavior indicators, individuals were clustered by their residential location preferences (Liao et al., 2015), individual lifestyles (Alemi et al., 2018), and attitudes towards mobility as a service (Alonso-González et al., 2020).

A few studies clustered individuals on the basis of activity patterns and trip chain complexity using LCA. Schneider et al. (2020) grouped the mobility patterns of individuals into several travel mode classes based on daily trip rates per travel mode and the proportion of reported non-travel behavior. Trip chain complexity then was analyzed for each identified class. Unlike other studies, Rafiq and McNally analyzed the heterogeneity in daily activity-travel patterns (the complete sequence of activities and travel made in a whole day) of public transit users (2021) and ride-hailing users (2022a) by categorizing their patterns into a set of classes using trip and tour-related indicators and then analyzing the demographic composition of each identified classes.

A similar approach was applied in this study to analyze the variations in activity patterns of telecommuters after the first year of the pandemic. In particular, we explored heterogeneity in the daily activity patterns of telecommuters considering all seven days of the week. We then compared all-day patterns with the patterns for weekdays only. The mathematical formulation of LCA, required variables, and model estimation results are discussed next.

Mathematical Formulation of Latent Class Analysis (LCA)

The Latent Class Analysis (LCA) *probabilistically* divides input samples (the population) into a given number of mutually exclusive and exhaustive latent classes (Lanza and Rhoades, 2013). Suppose a population of size N belongs to R classes. Let each member of a population (indexed by i) contain J *indicator* variables (indexed by j), each of which can take a value from a set of K_j possible outcomes (in LCA, all indicator variables should be categorical). Let $Y_{ijk} = 1$ if respondent i takes k-th outcome for its j-th categorical variable, and $Y_{ijk} = 0$ otherwise, where $j = 1,\ldots, J$ and $k = 1,\ldots, K_j$. Let ρ_r denote the probability that a respondent falls into a certain class r (called the *class membership probability*) and π_{jrk} denote the probability that observation in class *r* produces the *k*-th outcome on the *j*-th variable (called the *class-conditional probability*). In that, the likelihood of observing a certain respondent is given by:

$$f(Y_i|\pi,\rho) = \sum_{r=1}^{R} \rho_r \prod_{j=1}^{J} \prod_{k=1}^{K_j} (\pi_{jrk})^{Y_{ijk}} \quad \dots\dots\dots\dots\dots\dots\dots\dots..(1)$$

LCA estimates ρ_r and π_{jrk} using the maximum likelihood estimation (MLE) technique that tries to maximize the likelihood of obtaining the observed Y_i's as they are, which is given by the following equation (in logarithmic form):

$$\mathcal{L} = \prod_{i=1}^{N} f(Y_i|\pi,\rho) \Rightarrow \log \mathcal{L} = \sum_{i=1}^{N} \log f(Y_i|\pi,\rho) \quad \dots\dots\dots\dots\dots\dots\dots..(2)$$

Inserting the probability function from Eq (1), yields the following:

$$\log \mathcal{L} = \sum_{i=1}^{N} \log \left(\sum_{r=1}^{R} \rho_r \prod_{j=1}^{J} \prod_{k=1}^{K_j} (\pi_{jrk})^{Y_{ijk}} \right) \dots\dots\dots\dots\dots\dots\dots....(3)$$

In a more generalized LCA model, the class probabilities, ρ's, are regressed from a set of observed variables, called *covariates*, by using a multinomial logistic regression (MNL). The estimation technique would find a set of per class coefficient vectors, denoted by η_r for class *r*, instead of scalar ρ_r's, along with π_{jrk} (η_r is a vector of size *V*+1 per class for *V* covariates; one coefficient for each covariate plus an intercept term). The matrics $[\pi]$ and $[\eta]$ are called the *parameters* of an LCA model, and the model estimation, therefore, corresponds to finding them from the input dataset using the MLE technique mentioned above. In this study, we used the poLCA (Polytomous Variable Latent Class Analysis) package available in the statistical software R to estimate the LCA model parameters (Linzer and Lewis, 2011). More details on LCA formulation and its estimation technique can be obtained in (Rafiq and McNally 2021, 2022a).

Indicators and Covariates of the LCA Model

A set of indicator variables and covariates are considered in a latent class model. A latent class model is typically estimated in a combination of a measurement model and a structural model. A measurement model is estimated to define latent classes by using *indicator* variables. On the other hand, a structural model is estimated to predict the probability of an individual belonging to a latent class by using the model *covariates*. Figure 1 shows the conceptual latent class model and the set of indicator variables and covariates selected for this study.

As indicator variables, we considered various activity and trip-related attributes of telecommuters including the quarter of the year 2021 in which the travel occurred, at-home work start time, longest at-home work duration, number of at-home work segments, number of daily non-work trips, and out-home non-work activity start time. Since a telecommuter can make multiple at-home work activities and multiple out-home non-work activities in a day, to capture multiple start times of these activities, a set of binary variables were considered instead of a single categorical variable. Four binary variables including AM peak (6am – 10am), midday (10am – 3pm), PM peak (3pm – 7pm), and evening (7pm – 6am) periods were used to represent both work and non-work activity start time. To capture class membership profiles, a set of socio-demographic characteristics of telecommuters were used as covariates in the model that includes gender, age, household income, race, presence of children (<18 years old), household size, private versus public job holders, and full-time versus part-time workers.

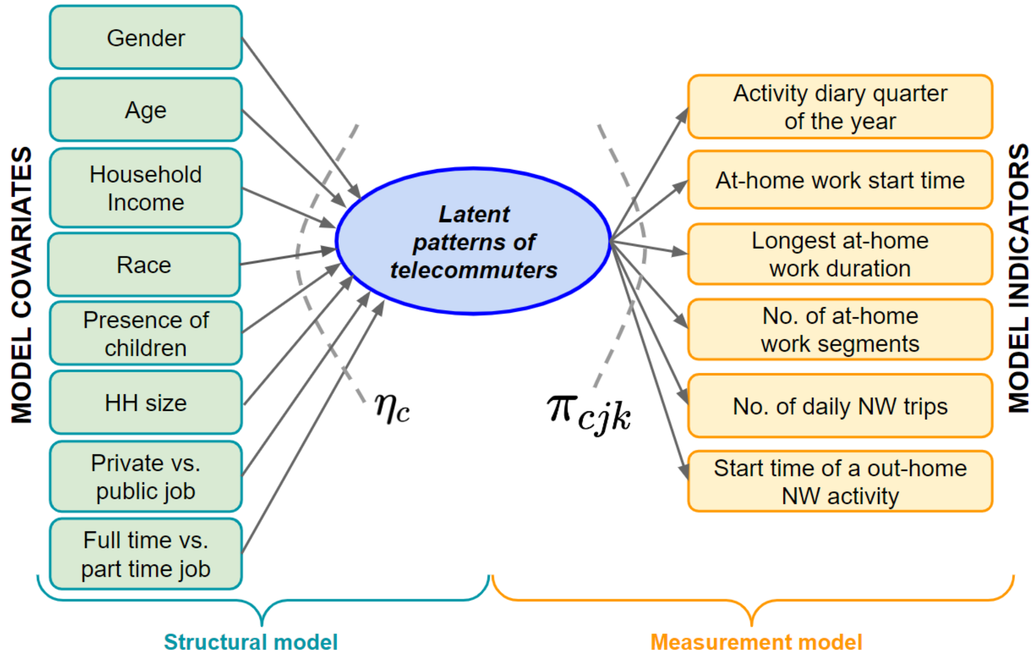
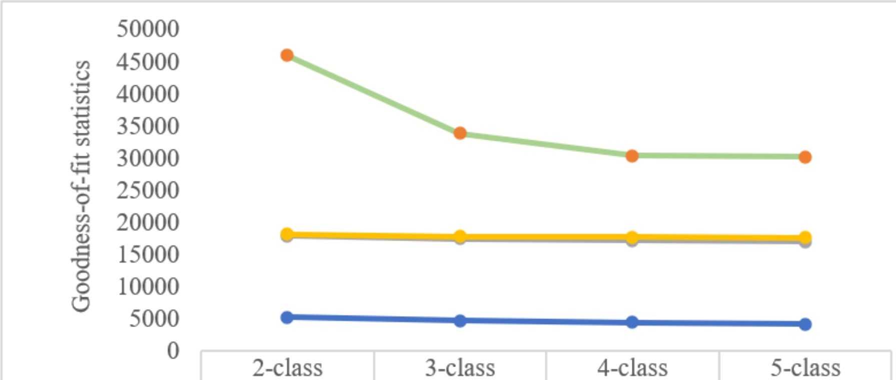


Figure 1. Latent Class Analysis (LCA) model

Estimation of the LCA model and Fit Statistics

The poLCA (Polytomous variable Latent Class Analysis) in the statistical software package R is used in this study to run the LCA model. R provides several goodness of fit measures including AIC (Akaike Information Criterion) (Akaike, 1973) and BIC (Bayesian Information Criterion) (Schwartz, 1978), which are the two most common and widely used fit measures. AIC and/or BIC are used to compare the relative fit of models with differing numbers of latent classes, where a lower value suggests a more optimal balance between model fit and parsimony (Lanza and Rhoades, 2013). Pearson's χ^2 fit and G^2 are also used as fit statistics, where preferred models are those that minimize the χ^2 and G^2 statistics without estimating an excessive number of parameters (Linzer and Lewis, 2011).

We estimated LCA models for two to five classes with a full set of indicators and covariates. We then observed the corresponding fit statistics and empirically assessed the interpretability of the resulting classes. Figure 2 shows the fit statistics for the two to five-class models. Although the five-class model has slightly lower AIC and BIC values than the three or four-class models, we accepted the three-class model for this study because it could be readily identified, had greater parsimony, and could be logically interpreted in terms of activity patterns of telecommuters. In addition, in four and five-class models, the additional classes did not show any meaningfully distinct characteristics in terms of activity patterns and socio-demographics compared to the three-class model.



	2-class	3-class	4-class	5-class
G2	5210.1	4677.5	4397.7	4148.8
Chi-square	45859.5	33768.4	30312.3	30148.1
AIC	17906.1	17436.7	17188.1	16968.9
BIC	18132.6	17806.0	17700.3	17623.8

Note: G^2, χ^2, AIC, BIC denote likelihood ratio chi-square statistics, chi-square value, Akaike Information Criterion, and Bayesian Information Criterion respectively.

Figure 2. Model fit statistics for two to five-class model

Results and Discussion

This section presents the model results, including (a) characteristics of the membership of the three identified classes (b) prediction of latent class membership, and (c) the activity-travel patterns of the three telecommuter classes.

Telecommuter Classes and Socio-Demographics

The three identified latent classes of telecommuters and their socio-demographics are summarized in Table 2.

Table 2. Summary of telecommuters by three latent classes (N = 1,017)

Class	Activity pattern class	Class probability	Class size	Socio-demographics in each pattern class
1	*Conventional-work patterns*	0.36	367	Workers from high-income households with children, employed in full-time public sector jobs who tend to have a conventional work schedule but make non-work activities, many in the PM peak.
2	*Flexible-work patterns*	0.33	335	Workers from low to medium income, non-Asian households working in private sector and part-time jobs whose work activities are not pre-dominate, with out of home non-work activities throughout the day.
3	*Work-only patterns*	0.31	315	Workers of middle to older ages, living in households without children, employed in full-time and public sector jobs, who primarily remain at home and maintain a conventional work schedule.

Note: Class probability is determined by the LCA model, which refers to the probability of an individual belonging to a particular class. Class size is calculated by assigning an individual to a class for which the probability of that individual belonging to that particular class is highest (modal assignment).

The class-conditional membership probabilities for the indicator variables (π_{jrk} table) and class-wise probability-weighted summary statistics for covariate variables are shown in Tables 3a and 3b, respectively. The class size was determined by assigning an individual to the class for which the probability of that individual belonging to that particular class was the highest (also known as modal assignment). The summary statistics are reported as probability-weighted mean values considering all individuals instead of computing the mean values of the individuals after assigning individual cases to the class with the highest probability.

Table 3a. Class-conditional membership probabilities for indicator variables (π_{jrk} table) (N = 1,017)

	Class 1	Class 2	Class 3
	Conventional-work patterns	Flexible-work patterns	Work-only patterns
Class probability	0.36	0.33	0.31
Indicator variables			
Activity diary quarter of the year			
Q1: Winter (Jan – Mar, 2021)	0.28	0.29	**0.44**
Q2: Spring (Apr – Jun, 2021)	0.27	0.23	0.15
Q3: Summer (Jul – Sept, 2021)	0.26	0.27	0.21
Q4: Fall (Oct – Dec, 2021)	0.19	0.21	0.20
At-home work start time			
AM peak (6am - 9am)	**0.90**	0.32	**0.76**
Midday (9am - 3pm)	**0.91**	0.33	**0.75**
PM peak (3pm - 7pm)	0.35	0.23	0.24
Evening (7pm - 6am)	0.22	0.26	0.24
Longest at-home work duration			
<= 120 minutes	0.05	**0.73**	0.17
121 – 240 minutes	0.44	0.14	0.31
> 240 minutes	**0.50**	0.14	**0.52**
Number of at-home work segments			
# of segment = 1	0.00	**0.82**	0.23
# of segment = 2	0.44	0.14	**0.43**
# of segment = 3 or more	**0.56**	0.04	0.34
Number of daily non-work trips			
# of trips = 0	0.13	0.11	**1.00**
# of trips = 1 – 2	0.42	0.34	0.00
# of trips = 3 or more	**0.45**	**0.55**	0.00
Out-home non-work start time			
AM peak (6am - 9am)	0.32	0.34	0.02
Midday (9am - 3pm)	0.30	**0.60**	0.03
PM peak (3pm - 7pm)	**0.63**	**0.49**	0.03
Evening (7pm - 6am)	0.31	0.17	0.00

Note: Class probability is determined by the LCA model, which refers to the probability of an individual belonging to a particular class.

The first telecommuter class was the largest identified (36 percent of 1,017) whose activity patterns were deemed *conventional-work-schedule* patterns. This group maintains a conventional "9-to-5" work schedule and make at least one out-of-home non-work activity, typically after the PM peak period (63 percent). Members of this class were employed in full-time (91.6 percent), public sector jobs (73.3 percent), and belonged to high-income households (58.4 percent) with children.

Table 3b. Class probability-weighted summary statistics for covariate variables (N = 1,017)

	Class 1	Class 2	Class 3
	Conventional-work patterns	Flexible-work patterns	Work-only patterns
Class size[a]	367	335	315
Covariates			
Gender of the telecommuter			
Male	**49.3**	**47.4**	**52.3**
Female	50.7	52.6	47.7
Age of the telecommuter			
18 – 35 years	26.9	27.5	19.5
35 – 45 years	31.1	27.9	31.2
> 45 years	**42.0**	**44.6**	**49.3**
Household income			
Low income (less than $40K)	5.9	15.5	10.4
Middle income ($40K - $100K)	35.7	37.3	40.6
High income (more than $100K)	**58.4**	**47.2**	**49.0**
Race			
White	77.4	80.9	77.5
Black	8.4	11.3	9.4
Asian and others	**14.2**	**7.8**	**13.1**
Presence of child (< 18 years old)			
Yes	**46.4**	**45.2**	**35.9**
No	53.6	54.8	64.1
Household size	2.58	2.73	2.46
Type of employment			
Private	**26.7**	**42.8**	**33.1**
Public	73.3	57.2	66.1
Type of worker			
Full-time	91.6	73.7	87.1
Part-time	**8.4**	**26.3**	**12.9**

Note: [a] Class size is determined by the modal assignment. Summary statistics are reported as probability-weighted mean values.

The second class corresponded to *flexible-work* patterns (33 percent of telecommuters) where, as the name suggests, work did not dominate on the day in question. This group appeared to have much more flexibility in terms of the work start time. The longest work duration for the majority of the telecommuters in this group was considerably lower (less than or equal to 2 hours for 73 percent of workers) than in the other two groups. This telecommuter group reported making multiple non-work trips on the travel day where these activities occurred throughout the day. This class comprised telecommuters who more frequently belonged to low to medium income households (15.5 percent were from low-income compared to 5.9 and 10.4 percent for the other two classes) and non-Asian households. Compared to the other two classes, a considerable proportion of telecommuters in this group worked in part-time (26.3 percent compared to 8.4 and 12.9 percent) and private sector jobs.

Finally, the third class was deemed *work-only* patterns with a 31 percent class probability. Similar to class 1, these telecommuters exhibited a conventional work schedule at home. However, this group did not make any non-work trips on the diary day, which implies that they stayed at home throughout the day (100 percent of these telecommuters reported zero trips). In terms of socio-demographic characteristics, these telecommuters were in middle to older age groups and lived in households without children. The majority of workers in this class were public sector job holders who were employed full-time.

Prediction of Latent Class Membership

The effects of covariates on class membership (η_r table) are presented in Table 4. Each of the identified latent classes corresponds to an underlying group of individuals who are characterized by a particular activity-travel pattern and social-demographics features.

Table 4. Prediction of latent class membership ($\boldsymbol{\eta_r}$ table) (N = 1,017)

Covariates	Flexible-work vs. conventional-work patterns	Work-only vs. conventional-work patterns
Intercept	-1.118	0.568
Gender of the telecommuter (baseline: Male)		
Female	-0.168	-0.197
Age of the telecommuter (baseline: 18-35 years)		
35 – 45 years	-0.050	0.562**
> 45 years	-0.022	0.480**
Household income (baseline: low income, < $40K)		
Middle income ($40K - $100K)	-0.809**	-0.420
High income (more than $100K)	-1.085***	-0.792**
Race (baseline: Asian and others)		
White	0.601**	-0.047
Black	0.804**	0.002
Presence of child (< 18 years old): Yes	-0.308	-0.698**
Household size	0.261**	0.160*
Type of employment (baseline: Public)		
Private	0.447**	0.185
Type of worker (baseline: Full-time)		
Part-time	1.144**	0.327

*, **, and *** indicate statistical significance respectively at 10%, 5%, and 1%.

Table 4 shows covariate coefficients for class 2 and class 3 relative to class 1 (i.e., conventional-work schedule was the reference group). An effect of age was found on the activity patterns. For example, middle to older (35 and over) age group telecommuters were more likely to belong to class 3 (work-only patterns) than class 1 (conventional-work patterns) compared to the younger age group (18 – 35 years). Unlike age, there was no significant impact of gender on activity pattern classes. Household income did affect class membership: those with higher income tended to belong to class 1 more than class 2 (flexible-work patterns) and class 3. In addition, compared to Asian and other races, White and Black racial groups were more likely to exhibit flexible-work patterns (class 2) than conventional-work patterns (class 1). Other household characteristics such as the presence of a child and household size had effects on a telecommuter's activity pattern choice. For instance, a telecommuter who belonged to a household without a younger child (<18 years) was more likely to be included in class 2 where no non-work trips were made during the travel day (work-only patterns). On the other hand, a telecommuter from a smaller household was more likely to be included in class 1 than the other two classes. We also found an association of employment characteristics with class membership, with people working in part-time private jobs, having a higher tendency to make flexible than conventional work patterns.

Activity-travel Patterns of Identified Classes

Next, the activity-travel patterns of the three identified classes were analyzed, including what activities (work and nonwork, at home or outside the home) and travel (trips for nonwork activities outside the home) were executed by individuals from a given class. A graphical representation, in the form of a 2D plot, is utilized for each class to show the sequence of *all* activity and travel reported in a travel diary day for 50 *randomly* selected individuals from that class. In the plot, the X-axis represents the timespan of a 24-hour day starting from 4 am to the next day at 4 am (a total of 1440 minutes) and the 50 individuals are stacked on the Y-axis with their activities and travel displayed in time from left to right as a chronological sequence of activities. Each activity and travel segment has a length equal to the duration of that activity and the activities are color-coded based on the activity type (work is red, nonwork is green, travel is blue, and staying home is gray). In the plot, the 50 individuals are sorted, in ascending order, by the starting time of an individual's first work segment of the day. With this illustration, the drawing captures a distinctive color pattern for each class—visually demonstrating the activity-travel and their sequences and durations on the day—which are referred to as *activity-travel patterns* for each class.

Since LCA is a probabilistic method, it does not partition samples into mutually exclusive classes like other clustering techniques (e.g., *k*-means clustering); instead, it assigns each sample to *all* classes but with different probabilities. In this, an individual sample was assigned to the class for which the probability of that individual belonging to that particular class was the largest (this is called *modal assignment*). Ideally, we would depict the plots for all individuals in the class but space and clarity of display limits this to a selection of 50 random patterns. We generate similar plots for 10 different random samples, each time yielding similar-looking plots. Figure 3 shows one such plot for each of the three classes. On the right-hand side of each pattern plot, we also display a *time-in-motion* plot for each class, which shows the percentage of workers in a class participating in an in-home or out-of-home activity at each point of time during the day.

Class 1. "Conventional-work" patterns

Class 1 reflects of conventional work schedule teleworkers, each of whom started their work in the morning at home (red segments) and continued the work till the afternoon (4 pm to 6 pm), with occasional midday short breaks in between work segments. The time-in-motion plot shows that about 80 percent of individuals in this class start their work by 10 am and are mostly done with work after 6 pm. The members of this class occasionally made trips outside their home (blue segments) for non-work activities (green segments) but the activities occur mostly after work within the 4 pm to 10 pm window (see Figure 4a where blue/green occurs mostly after red in the pattern drawing). This class mostly remained home with an average dwelling time at home of about 1316 minutes (about 22 hours) in a day.

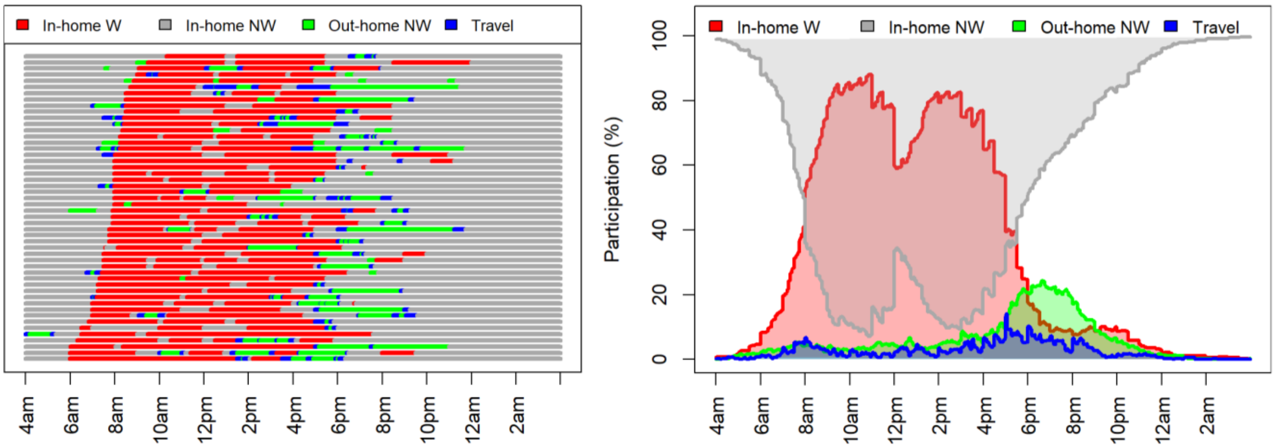
Class 2. "Flexible-work" patterns

Figure 4b shows the activity-travel patterns of individuals who demonstrate a higher degree of flexibility in their work schedule. Unlike other classes, they did not necessarily start work in the AM peak hours (6 am – 9 am), but rather distributed their work throughout the day. A majority of them had a single work segment where the work segment duration was quite short (82 percent had only one work segment and 73 percent reported the longest work duration of less than or equal to two hours). They also had the smallest total work duration in a day (average work duration per day was 2.1 hours compared to 8 hours and 7.5 hours for class 1 and class 3, respectively). This group makes multiple trips and performs non-work activities outside their home, usually during midday and PM hours (55 percent of class members did make three or more trips). This class has on average 2.7 hours of non-work activities outside home whereas class 1 spent about 1.4 hours for the same. Moreover, this class had about 64 minutes of travel during a day compared to 38 minutes for class 1 (class 3 did not make any travel). As a result, this class stayed less time at home compared to the other two classes (their home dwell time is 20.3 hours versus 21.9 and 24 hours for class 1 and class 3, respectively).

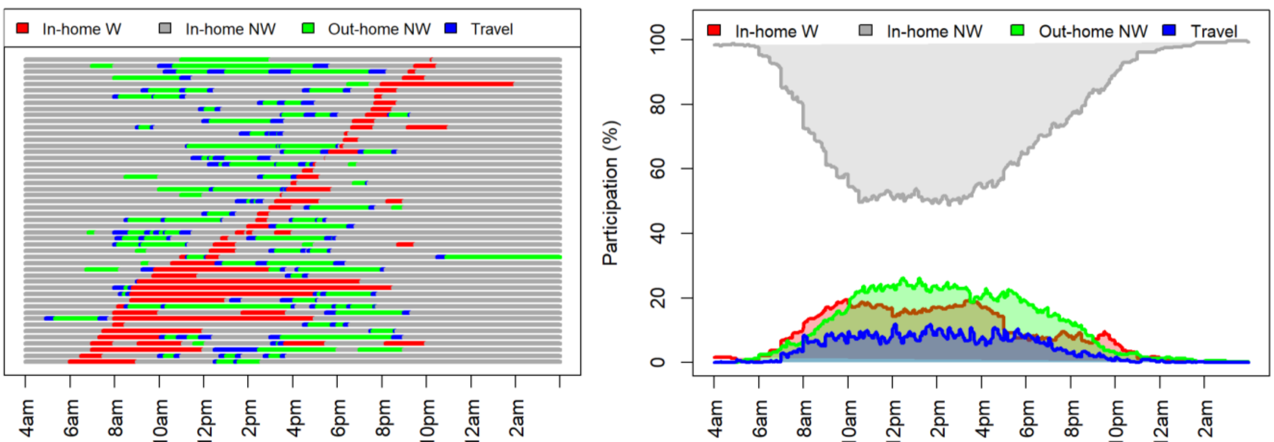
As part of this class's distinct activity-travel pattern, outside home non-work activities and travel either preceded and followed work segments of the day (blue/green segments around red segments in the drawing). It is interesting to note that the majority of workers in this class were surveyed on a weekend day (69 percent, versus 9 and 18 percent for class 1 and class 3, respectively). This is might be another reason why the schedule appears to be so flexible in terms of work segments. The time in motion plot reveals that the fraction of people in the class stayed home at any given time in a day is far smaller than the same of class 1 and class 3, because they performed their out-of-home activities throughout the day. The plots also show that the fraction of people engaged in work at any given time of the day is smaller and the fraction of people outside home activities is larger than the other two groups.

Class 3: "Work-only" patterns

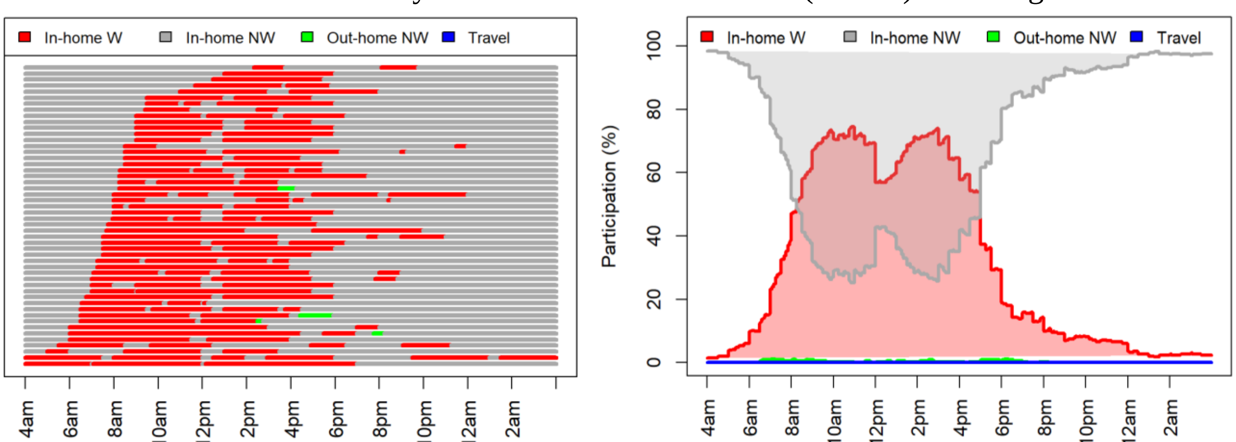
This is the activity-travel pattern of individuals who spent their entire time at home without reporting any trips outside home during the 24-hour day. They perfromed work and non-work activities both at home (this class had zero trips, whereas class 1 and class 2 made on an average 3.0 and 3.4 trips per day). Unlike conventional teleworkers (class 1), the members of this class shifted a little from their dense AM peak work schedule (76 percent started their work at AM peak window (6 am – 9 am), whereas for class 1 this was 90 percent). They rarely reported out-of-home non-work activities without making any trip (occasional green segments on the activity-pattern chart). Interestingly, a large fraction of individuals in this class (44 percent) reported their diary day during the first quarter of 2021 (January to March, 2021) when the COVID-19 spread remained high as vaccines were being introduced. This might be the reason, in part, why they stayed home all day without reporting any outside travel while working full time from home (average work duration is 8 hours).



a) Class 1. "Conventional-work" patterns: 50 random patterns on the left and time in motion by activities for the entire class (N=367) on the right



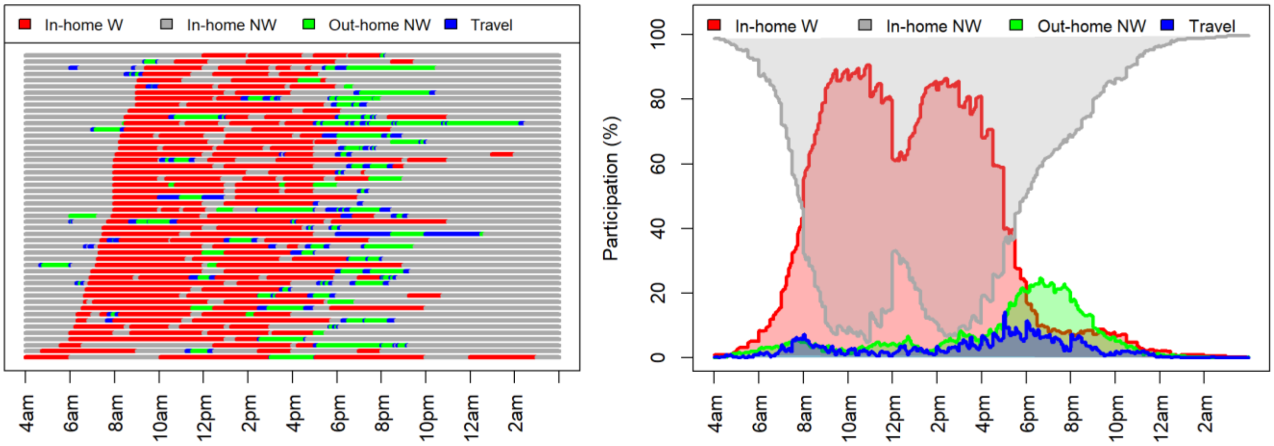
b) Class 2. "Flexible-work" patterns: 50 random patterns on the left and time in motion by activities for the entire class (N=335) on the right



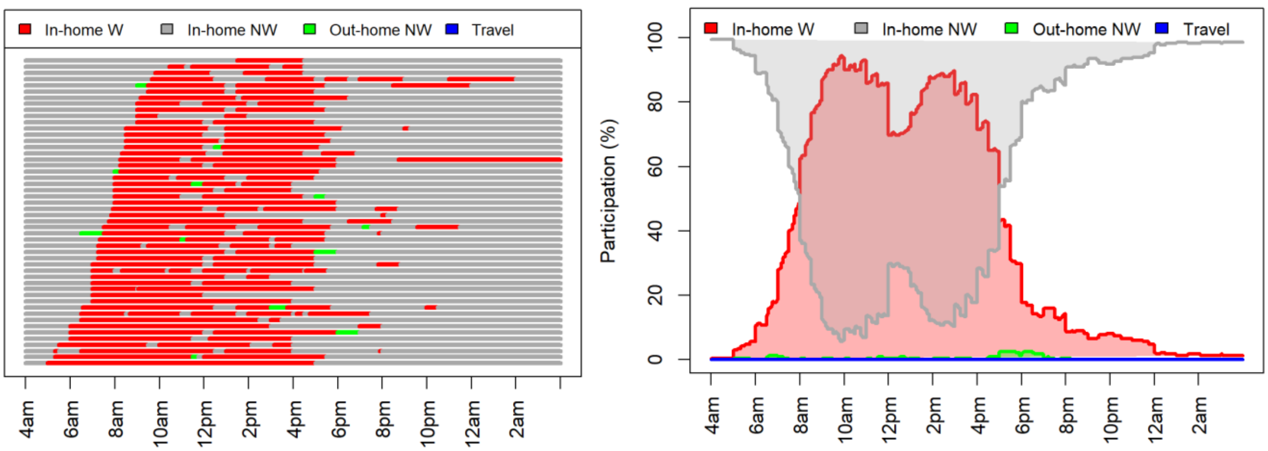
c) Class 3. "Work-only" patterns: 50 random patterns on the left and time in motion by activities for the entire class (N=315) on the right

Notes: W and NW refers to work and non-work activities respectively. These figures read better in color.

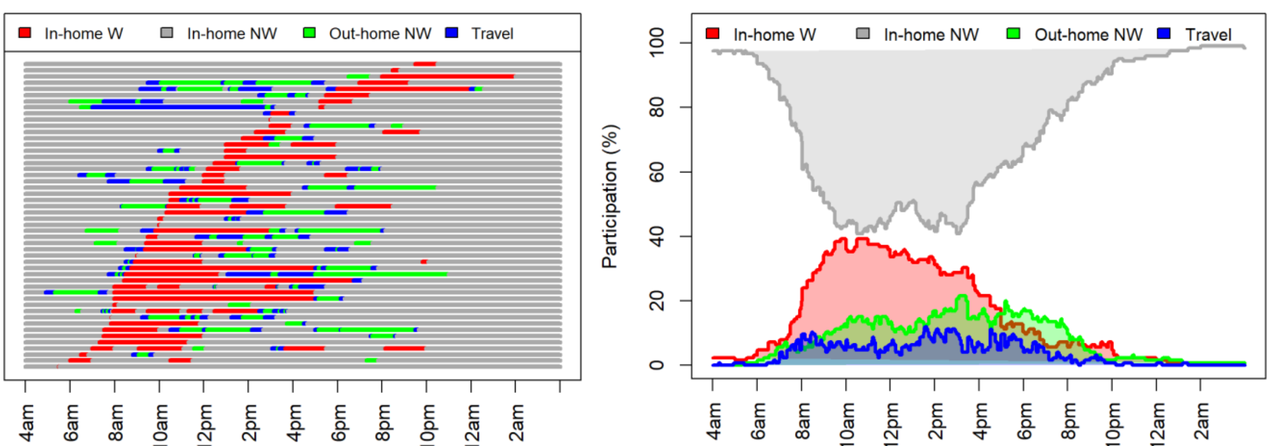
Figure 3. Sampled activity patterns and time in motion for activities by telecommuter classes on *all seven days of the week.*



a) Class 1. "Conventional-work" patterns: 50 random patterns on the left and time in motion by activities for the entire class (N=316) on the right



b) Class 2. "Work-only" patterns: 50 random patterns on the left and time in motion by activities for the entire class (N=232) on the right



c) Class 3. "Flexible-work" patterns: 50 random patterns on the left and time in motion by activities for the entire class (N=125) on the right

Notes: W and NW refer to work and non-work activities, respectively. These figures read better in color.

Figure 4. Sampled activity patterns and time in motion for activities by telecommuter classes for *weekdays only*.

In a separate analysis, an LCA was executed with individuals that reported week-day only (Monday through Friday) activity. It is observed that the general activity patterns for the three derived classes remained similar with only changes in group membership probabilities. Figure 4 shows the *weekday* activity-travel patterns and the time-in-motion plot for the three classes, which appear identical to the *all-day* activity patterns displayed in Figure 3.

Conclusions

Working from home (WFH) or telecommuting has long been advocated by planners and policy makers as an effective travel demand management strategy and an environmental management tool to reduce travel and greenhouse gas emissions. Due to the current outbreak of the COVID-19 pandemic and its subsequent travel restrictions, WFH has become an important alternative work arrangement. In this context, this study utilized Latent Class Analysis (LCA) to examine heterogeneity in the activity-travel patterns for people working from home (telecommuters) in the 2021 post-vaccine period. The term *pattern* represents the complete sequence of activities and travel made by a telecommuter over a full day. Based on the 2021 ATUS data, the LCA model results suggest that the patterns of telecommuters can be divided into three distinct classes. Class 1 was composed of workers from high-income households with children, employed in full-time public sector jobs, and who tend to have a conventional work schedule but make non-work activities typically during the PM peak period. Workers from low to medium income, non-Asian households, working in part-time private sector jobs constituted Class 2, where work activities were not pre-dominant but out-of-home non-work activities were spread throughout the whole day. Finally, Class 3 members were workers of middle to older age, living without children, working in full-time public sector jobs, who primarily remain at home during the day and maintained a conventional work schedule.

The changes in our work behavior imposed by the pandemic are anticipated to make the post-pandemic workplace experience somewhat different than the pre-pandemic era with greater accommodation of teleworking and other changes in our travel demand. In this context, the results of our analysis of activity patterns could help policymakers to identify particular groups of workers based on their demographics, recognize how they responded to changes in activity-travel scheduling imposed by the pandemic, and understand what might be their particular travel needs at different times in a day. This could facilitate the development of policy initiatives to manage relevant transportation and land-use related demands in the current and post-pandemic periods. In addition, The activity-travel pattern analytical method and visualization techniques used in this study represent a new and valuable graphic display for future research.

As with most studies, there are some limitations in this research. Since ATUS data contains single-day diary data, the activity-travel patterns reported in the ATUS is specific to the survey date. Research does suggest that single-day travel surveys of appropriate sample size can capture the underlying distribution of behaviors. While the day in question may not be typical of an individual respondent, the sum total over all respondents can capture the overall distribution.

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Author Contribution Statement

The authors confirm contribution to the paper as follows: study conception and design: R. Rafiq, M. G. McNally; data processing: Y.S. Uddin and R. Rafiq; analysis and interpretation of results: R. Rafiq, M. G. McNally, and Y.S. Uddin; draft manuscript preparation: R. Rafiq, M. G. McNally, and Y.S. Uddin. All authors reviewed the results and approved the final version of the manuscript.

Conflict of Interests

On behalf of all authors, the corresponding author states that there is no conflict of interest.

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