Who Would Continue to Work from Home in Hong Kong

As the COVID-19 Pandemic Progresses?

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ABSTRACT

This study aims a more thorough understanding of individuals' motivations and determinants of working from home (WFH) at various phases of the pandemic. To achieve this research goal, we analyze attitudes towards WFH, the profiles of various types of workers engaged in WFH, and the determinants of the current and future expected frequency of WFH among 816 workers in Hong Kong. We identify four types of teleworkers: (1) those with little employer support, (2) those distracted with tech problems, (3) those with good home office, and (4) those with substantial employer support. Separate latent-class choice models present that WFH frequencies in early phases of the pandemic (and at the moment), attitudes towards WFH, and certain constraining/facilitating factors affect the (expected) frequency of WFH. This study provides valuable insights into the types of teleworkers and the determinants of WFH, which will help policymakers create ways to encourage (or discourage) the future frequency of WFH.

Keywords: COVID-19; Working from home; Attitudes; Latent-Class Cluster Analysis; Latent-Class Choice Model; Hong Kong

1. INTRODUCTION

Working from home (WFH), also referred to as teleworking, telecommuting, and working remotely, has often been promoted as a way to reduce daily travel and address congestion problems (Choo et al., 2005; Elldér, 2020; Lachapelle et al., 2018); however, it has increased rather slowly over the past several decades (Messenger & Gschwind, 2016; Vilhelmson & Thulin, 2016). This slow progression away from in-office work can be partially explained by the large number of jobs that are unsuitable or difficult to perform from home, resistance by management (e.g., fearing less control over employee performance), and reluctance of employees to work from home for several reasons: less contact with co-workers, a less than ideal work environment at home, and potential distractions and stress from spouse and children, social isolation, and limited physical activity (partly because (active) travel to work disappears) (Conway et al., 2020; Shamshiripour et al., 2020). In addition, studies have shown that teleworking might result in work intensification and a greater inability to switch off (Felstead & Henseke, 2017).

The obligation of many people to work from home as one of the measures preventing the spread of COVID-19, together with improved technology, has shown employees and employers that teleworking can be a feasible alternative to commuting to the workplace. Note that the frequency of working from home increased substantially for most workers during the pandemic and that a large share of workers did not commute anymore. For instance, in a survey in the United States, those who worked from home increased from 37% pre-pandemic to 58% for April-October 2020 and stayed at 53% for November 2020-May 2021 (Javadinasr et al., 2021); In Australia, the share of non-teleworkers in a survey fell from 57% in the early March 2020 to 11% since the late March 2020 as the country implemented measures for international and non-essential travel (Hensher et al., 2021); In Asia, 80% of survey participants in Indonesia engaged in teleworking or e-learning more for March-April 2020 than before (Irawan et al., 2021); and in Europe, 6% of survey respondents in the Netherlands worked “almost all their hours from home” in 2019, but their proportion rose to 39% for March-April 2020 (de Haas et al., 2020). Although the frequency of working from home is now gradually decreasing (e.g., in the U.S., those who worked entirely from home reduced from 54% in May 2020 to 25% in September 2021 (Saad & Wigert, 2021)), most people expect to be working from home more frequently in the future compared to pre-COVID-19 (Mohammadi et al., 2022), although this may depend on elements such as type of work and workers’ experience with working from home (Georgescu et al., 2021). As a result, it can be expected that the COVID-19 pandemic will be a catalyst for teleworking and that more people will telework at least a few times a month after the pandemic (Beck et al., 2020; De Vos, 2020; Elldér, 2020; Hodder, 2020). While the potential outcomes of WFH on travel behavior have been widely discussed, factors leading to (continued) adoption of WFH remain largely unclear. As more WFH has occurred since the beginning of the COVID-19 pandemic and can be expected to continue, an analysis of the determinants of WFH could benefit future policies and decisions of both employers and governments.

This study aims a more thorough understanding of individuals’ motivations and determinants of WFH at various phases of the pandemic. To achieve this research goal, we analyze attitudes towards WFH, the profiles of various types of workers engaged in WFH, and the determinants of the current and future expected frequency of WFH among 816 workers in Hong Kong. With factor and cluster analyses, we examine attitudes towards the various elements of WFH and describe the profiles of distinct types of workers. In addition, with latent-class choice models, we investigate the effects of past (current) frequency of WFH, attitudes towards WFH, and certain constraining/facilitating factors on the (expected) frequency of WFH. In brief, this study provides new insights into the determinants of WFH and helps planners and policymakers develop measures that either promote WFH or discourage it.

The remainder of this paper is organized as follows: Section 2 summarizes recent findings in the literature about key factors behind the adoption of WFH, Section 3 describes the used data and methodology, Section 4 presents the main results, and Section 5 discusses implications to the literature and practice, and Section 6 concludes with limitations and future research directions.

2. LITERATURE REVIEW

The decision to work from home may be influenced by several factors (Figure 1), one of which is the influence of past behavior. Those frequently WFH before the pandemic or during the pandemic will be more inclined to keep doing so in the future. Past behavior is a strong determinant of future behavior, and behavior frequently performed (in a satisfying way) often becomes habitual. Several studies have found that those who frequently worked from home before the pandemic, or at least those who had the choice to do so, are more inclined to work from home during the pandemic and expect to do so after the pandemic (Beck et al., 2020; Conway et al., 2020; Nguyen, 2021). The COVID-19 pandemic may have created a change in context, which may have triggered a change in behavior (i.e., towards WFH). Since many employers and employees may have adjusted to the new (stable) norm of WFH, it may (have) become habitual to many.

Another factor influencing WFH is workers' attitudes, which strongly affect their intention to behave in a certain way (Ajzen, 1991). Positive attitudes towards a certain behavior have a positive effect on the intention to perform that behavior. As a result, those with a positive stance towards WFH, online meetings, and technology may be more inclined to work from home than those with a positive attitude towards working at the office, meeting co-workers in person, and commuting. One study (Beck et al., 2020), for instance, found that attitudes towards WFH had significant effects on the frequency of WFH in Australia even though certain population groups were forced to work from home. Another study (Nguyen, 2021) found that once the pandemic ends, those concerned about air quality in Hanoi (Vietnam) are more inclined to work from home than those who are not, and workaholics and those enjoying contact with co-workers intend to commute more frequently and work less frequently from home.

The decision to work from home is also determined by certain constraints and facilitators that may prevent or stimulate individuals to work from home. That is, WFH is influenced by existing barriers and enablers that either disable or enable WFH. For example, those with essential jobs (e.g., those in the hospitality industry) are typically not able to perform their jobs at home, and those with limited space at home or unreliable internet connectivity may find it difficult or impossible to work from home (Conway et al., 2020; Rubin et al., 2020; Shamshiripour et al., 2020). In general, those in technical and trade occupations tend to have a low probability of WFH (Beck et al., 2020). Conversely, those with employers who offer incentives to work from home promote more WFH (Beck et al., 2020): e.g., employers that allow their employees to work at alternative locations other than the regular workplace (Nguyen, 2021). In the meantime, residential locations account for the extent to which WFH helps workers save on travel time and costs. For example, those residing far away from their workplace might be more inclined to telework than those living closer to limit the time and money that they spend on commuting (Nayak & Pandit, 2021; Nguyen, 2021). Teleworking may also result in their relocating to more desirable residences farther from their workplace, resulting in fewer, yet longer commutes mostly covered by motorized transport (de Abreu e Silva & Melo, 2018; Ory & Mokhtarian, 2006; Zhu, 2013). Additionally, they might be more receptive to taking a new job previously regarded as too far away from their place of residence.

Except a few recent studies (Barbour et al., 2021; Beck et al., 2020; Nayak & Pandit, 2021; Nguyen, 2021), the travel behavior literature is still limited in a systematic and rigorous investigation of various determinants of WFH during and after the COVID-19 pandemic. Some studies point to savings on travel time and travel costs as important reasons for working from home (Nayak & Pandit, 2021; Vyas & Butakhieo, 2021); however, in-depth analyses of working from home determinants during the pandemic seem to be lacking. In this context, studies on these determinants via a mix of analytical approaches could provide valuable insights into effective policy responses that promote continued WFH for now and in the post-COVID era.

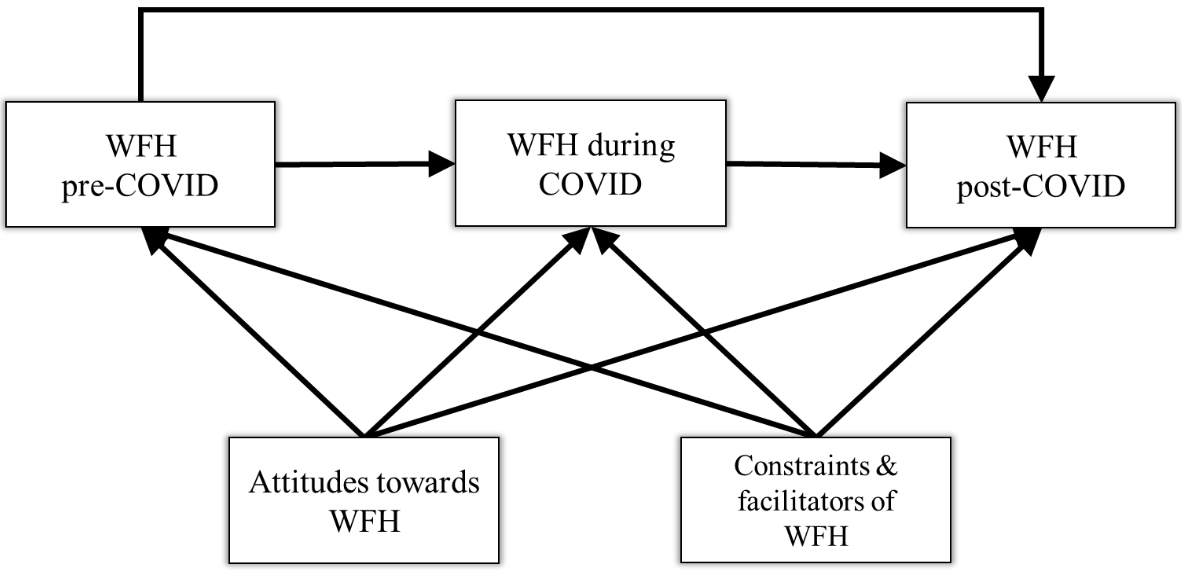


FIGURE 1 Conceptual model representing the effect of past behavior, attitudes, and constraints and facilitators on WFH pre, during, and post-COVID.

3. DATA & METHODS

3.1. *Data*

This study employs a dataset from a recent survey administered from December 5^{th} 2020 to January 5^{th} 2021, or during the fourth wave of infections in Hong Kong. Figure 2 presents daily new confirmed COVID-19 cases and deaths per million residents in Hong Kong from January 28, 2020 to August 2, 2022. In Hong Kong, the first case was confirmed on January 23^{rd}, 2020 in a 39-year-old male who traveled from Wuhan, China (E. Cheung, 2020). In response, the government implemented preventive measures that would reduce virus transmission in communities including border control, work from home mandate or recommendation for employees at non-essential tasks, closing/switching to online classes of schools and universities, closure of high-risk businesses, and size limits to social gatherings for much of January to April, 2020 (T. Cheung et al., 2020; OT&P Healthcare, 2022; Tsang et al., 2020). As a result, trends in cases and deaths during the first two infection waves in Hong Kong were relatively mild (1,037 cases and four deaths for January to April, 2020), compared to those in the North America and Europe. By contrast, in the early July 2020 cases and deaths started to rise substantially (3,605 cases and 82 deaths for July to August, 2020) (Dong et al., 2020), and these trends led the government to adopt stricter non-pharmaceutical intervention (NPI) measures such as whole-day dine-in ban at restaurants, mask mandate both indoors and outdoors, and the maximum gathering size down to two people.

After the gradual easing of NPI measures from the early September, 2020 and one-digit cases and no deaths on most days until the early November, 2020, the fourth infection wave started in the late November 2020 by more than 600 cases linked to a cluster of local dance clubs (Duhalde et al., 2021; Low, 2020). On December 3^{rd}, 2020, the education bureau announced the closing of all schools until 2021 (Ting et al., 2020), and on December 10^{th}, 2020, strict NPI measures were reintroduced (e.g., the maximum public gathering down to two people, no dine-in after 6 PM, and closure of the indoor sport facilities and similar businesses considered having high transmission risk) (HKSAR, 2020). During the data collection period from December 5th, 2020 to January 5th, 2021, Hong Kong reported 2,247 cases and 41 deaths (Dong et al., 2020). With continuing increases in cases and deaths, on January 23rd, 2021, the government first issued a stay-at-home order for a few residential blocks and performed mandatory tests for all residents (i.e., local lockdown) (O. Wong et al., 2021). While the government started to ease some of the earlier NPI measures in February, 2021, occasional super-spreading events and local infection clusters had the government implement local lockdown and postpone further easing until May, 2021 (OT&P Healthcare, 2022).

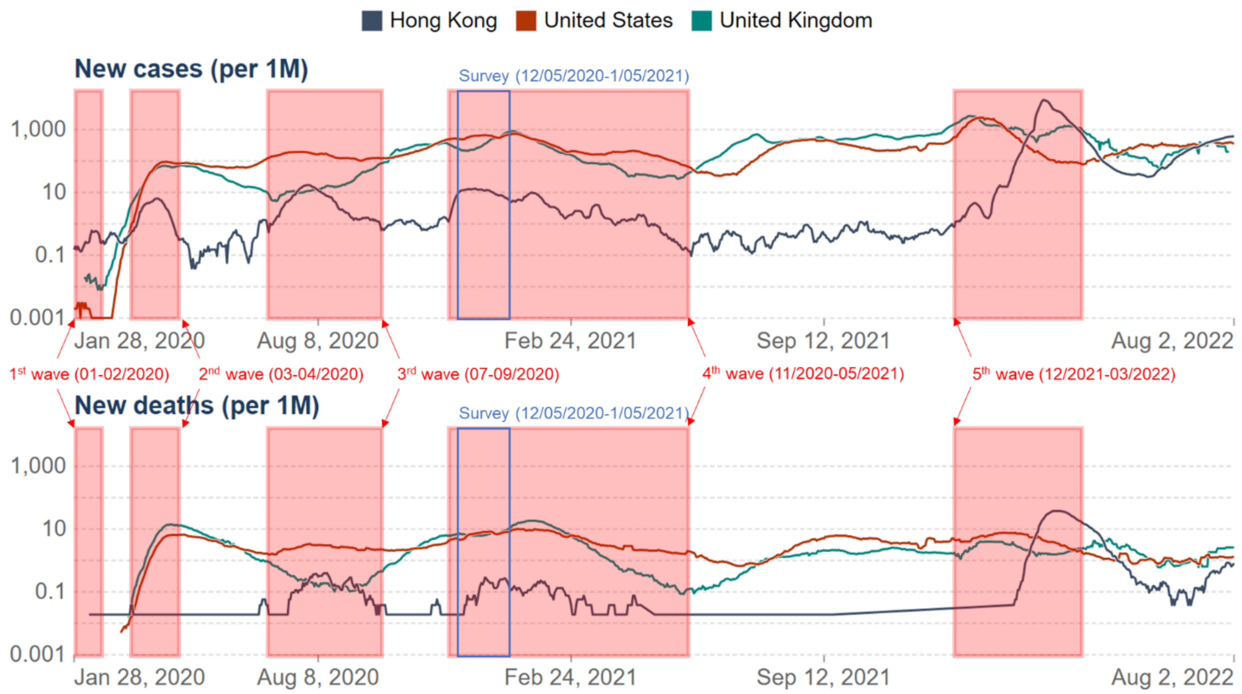


FIGURE 2 Daily new confirmed COVID-19 cases and deaths per million people.

Notes: 1. Values indicate seven-day rolling averages. 2. The vertical axis is in the logarithmic scale. 3. Specific periods for local infections/deaths and the survey administration are added in red and blue. The starting/ending months of the five infection waves are determined based on government announcements on non-pharmaceutical intervention measures (e.g., school/business closure, work-from-home mandates, and size limits to social gatherings). 4. Trends for the United States and the United Kingdom are added for comparison purposes. 5. Data come from Johns Hopkins University CSSE COVID-19 Data. 6. The chart image is obtained from Our World in Data (https://ourworldindata.org/coronavirus#explore-the-global-situation), to which the authors added the wave and survey periods.

The goal of the survey is to determine whether and to what extent temporarily adopted behaviors during the pandemic will last as the pandemic progresses. To achieve this goal, we designed a rich survey with eight sections on the following topics: attitudes on various items, use of information and communication technology (ICT) devices and services, work arrangements, household composition and childcare, shopping channels, typical travel behavior, access to vehicles, and basic socioeconomics and demographics. We administered the survey on an online survey platform (Qualtrics) in both English and Chinese, and provided an incentive of HK$100 grocery e-vouchers (equivalent to US$12.85) via random drawing.

We targeted the adult population living in Hong Kong at the time of data collection, and we recruited respondents via advertisements on a social network service (SNS) with the largest customer base in Hong Kong, Facebook. We chose Facebook mainly because of its time/cost-efficiency in reaching out to a large pool of potential participants. Given the extreme uncertainty in the progress of the pandemic and constant changes in government responses, we decided to expedite data collection not to miss a unique chance of observing behaviors, choices, and underlying attitudes at the moment. However, while SNS ads allowed us to recruit many of those who are familiar with ICT-enabled substitutes for in-person on-site activities (e.g., WFH, e-learning, and online shopping), its sampling frame appears not representative of the population in Hong Kong. That is, collected cases are biased towards younger, educated, and tech-savvy individuals with relatively low opportunity costs of time or strong interest in/motivation for taking surveys online (see Table 1). In addition, Facebook exposes ads to certain segments of users, whom they find more responsive to such ads based on past responses. That is, the sampling frame is a *subset* of Facebook users in Hong Kong who checked in on the service from December 5th, 2020 to January 5th, 2021.[1] While our sampling frame is biased and

[1] From December 5th 2020 to January 5th 2021 our Facebook ads were presented to 93,154 unique users (18 years old or older living in Hong Kong at the moment) for 217,963 times, and these users responded to the ads with 6,808 “clicks”. During this period, our online survey on Qualtrics (linked to the ads) collected 2,041 finished responses (i.e., those that reached the end of the survey with a reasonable time and were submitted) in

summary statistics are not generalizable to the entire adult population in Hong Kong, we believe statistical analysis still allows us to examine the relationships between changes in work arrangements and key factors (e.g., attitudes towards WFH).

After a comprehensive quality check of responses, we employ a sample of 816 full/part-time workers (excluding foreign domestic helpers), whose occupations were asked in an open-ended question and manually classified as one of white-collar, essential, public/education, or others. Some of frequent answers we assigned to each occupation category are like the following.

- White-collar: administrative staff, clerk, social worker, accountant, consultant, banker, and financial manager
- Essential: healthcare worker, salesperson, food & beverage industry, mechanic/technician, transportation (e.g., driver), warehouse, and logistics
- Public/education: government employee, teacher, and private tuition tutor,
- Others: freelancer

We also asked residential and workplace locations in geographic coordinates with Google Maps embedded in the survey. To each case, we appended population and job density measures at the small tertiary planning unit group (STPUG) level, extracted from the 2016 Hong Kong Census (an average STPUG accommodates 11,726 households and 34,278 residents as of 2016).

In this study, we focus on the intensity of working from home at four timepoints: "before the 3rd wave of the COVID-19 pandemic (before July 2020)", "during the 3rd wave of

total. Out of the 2,041 responses, we filtered out incomplete/unreliable ones and built a sample of 1,053 responses (including 816 workers and 237 non-workers) that passed various quality checks.

the COVID-19 pandemic (July-September 2020)", "currently" (December 2020), and "in April 2021". In the survey, the first three questions asked the respondents to recall/report the number of days WFH in a typical week (from zero to seven) and the last asked them to choose their near-future expectations on a 5-point scale compared to their present practice (from much less to much more *than the present*). While retrospective questions may collect less accurate information about past behaviors (compared to asking behaviors at the moment), we did so to investigate the effects of past behaviors on the current/near-future behaviors. After all, unlike a small number of panel data available at the moment (Matson et al., 2021; Molloy et al., 2021), we did not have access to any former respondents, who participated in similar surveys before the pandemic. Thus, while not ideal, we adopted retrospective questions, the only feasible way to collect critical information about past behaviors. Note also that we did not ask specifically about pre-pandemic WFH frequencies, which was a survey design flaw. Thus, our measures of past WFH frequencies may have been already higher than the pre-pandemic level.

Table 1 presents the summary statistics of the four WFH measures and the various factors that account for these measures for the worker sample (N=816). While official estimates on pre-pandemic WFH adoption patterns and frequencies would put the following measures in context, such estimates are not available in Hong Kong in part because of their limited practice (Planning Department, 2002). For instance, a 2018 survey by a consulting firm reports 85% of respondents in Hong Kong not having options for flexible work arrangements including WFH (randstad, 2018). A recent study in Hong Kong, whose sample is not representative of all workers, finds that the proportion of teleworkers among information workers increased from 3% in 2000 to 25% in 2015 (Leung & Zhang, 2017). This 22-percentage-point increase is substantial; however, it needs to be put in context. In Hong Kong, information workers belong to either professionals or associate professionals, whose combined share in all workers is 33.5% in 2019 (Census and Statistics Department, 2023). That is, the proportion of teleworkers among all workers could be 8.4 % (i.e., 25% of 33.5%) at the largest. While this number is not trivial, it is not as high as some latest statistics reported during the pandemic. In the meantime, Hong Kong records 78 hours of time lost per year due to congestion in 2021, comparable to Paris, New York, and London (82, 80, and 75 hours, respectively) (TomTom, 2022), and latest air quality measures present "Moderate" to "Unhealthy for sensitive groups" levels with $PM_{2.5}$ 26.6 μg/m^3 for the last year and 122.7 μg/m^3 for the last 30 days (Berkeley Earth, 2022).

TABLE 1. Summary Statistics of Key Variables (N=816).

Variable	*n(case)*	*share (%)*	*Variable*	*n(case)*	*share (%)*
WFH frequency			*Socioeconomics & demographics*		
December 2020 (base: no WFH) (*4*)[1]	381	46.9%	Age (base: 18-24) (*16*)[1]	91	11.4%
1-2 days a week	198	24.4%	25-34	300	37.5%
3-4 days a week	138	17.0%	35-44	256	32.0%
5+ days a week	95	11.7%	45-54	113	14.1%
July-Sep. 2020 (base: no WFH) (*6*)[1]	344	42.5%	55-64	37	4.6%
1-2 days a week	216	26.7%	65 or older	3	0.4%
3-4 days a week	160	19.8%	Place of birth (base: Hong Kong) (*1*)[1]	728	89.3%
5+ days a week	90	11.1%	Mainland China	71	8.7%
before July 2020 (base: no WFH) (*4*)[1]	559	68.8%	all others	16	2.0%
1-2 days a week	139	17.1%	Education (base: less than Bachelor's) (*17*)[1]	230	28.8%
3-4 days a week	56	6.9%	Bachelor's	387	48.4%
5+ days a week	58	7.1%	Postgraduate	182	22.8%
April 2021 (compared to December 2020) (*2*)[1]			Housing size (base: below 100 sqft) (*1*)[1]	19	2.3%
Much less often	133	16.3%	100-300 sqft	145	17.8%
Somewhat less often	165	20.3%	301-500 sqft	291	35.7%
About the same	327	40.2%	501-700 sqft	249	30.6%
Somewhat more often	161	19.8%	701-900 sqft	67	8.2%
Much more often	28	3.4%	901-1100 sqft	28	3.4%
Job attributes			More than 1100 sqft	16	2.0%
Work status (base: non-worker) (*0*)[1]			*Neighborhood type*		
full-time worker	688	84.3%	When growing up: urban (*0*)[1]	646	79.2%
part-time worker	117	14.3%	Suburban	97	11.9%
Study status (base: non-student) (*0*)[1]			Rural	73	8.9%
full-time student	52	6.4%	At the moment: urban (*6*)[1]	628	77.5%
part-time student	40	4.9%	Suburban	113	14.0%
Job nature (base: white-collar) (*26*)[1]	497	62.9%	Rural	69	8.5%
essential jobs	126	15.9%	Preferred in the long term: urban (*5*)[1]	577	71.1%
education/public officials	139	17.6%	Suburban	156	19.2%
all others	28	3.5%	Rural	78	9.6%
Commute attributes			*Built-environment attributes*		
Commute times (in minutes)[2] (*15*)[1]	41.848	22.323	People/square kilometer at home[2,3] (*309*)[1]	51,933	36,646
Primary mode (base: rail) (*11*)[1]	400	49.7%	Job/square kilometer at work[2,3] (*318*)[1]	51,923	66,359
bus	318	39.5%			
active modes	59	7.3%			
automobiles	20	2.5%			
all others	8	1.0%			

Notes:
1. Denotes the number of cases with missing values for a given variable. For the categorical variables, shares are computed only for those cases with non-missing values.
2. Indicates a continuous variable for which this table reports the mean and standard deviation (computed for cases with non-missing values only).

3. Denotes the density (i.e., the number of residents or jobs per square kilometer) at the small tertiary planning unit group (STPUG) for the *reported* geographic coordinates. Some 37.9% (=309/816) and 39.0% (=318/816) of respondents did not report the geographic coordinates of their homes and workplaces, respectively.

3.2. *Methods*

In this study, we answer the following questions to more thoroughly understand the attitudes towards, the current adoption of, and the near-future expectation for WFH.

1. Are the attitudes towards WFH positive, negative, or neutral?
2. How are the attitudes towards, frequency of, and job nature related to WFH associated with one another, and what distinct subgroups do they form in the sample?
3. How would these subgroups (identified in 2) predict the frequency of WFH in the future?
4. What factors account for the current frequency of WFH?
5. What factors account for near-future expectations for WFH?

To answer the above questions, we employ three methods. First, an explanatory factor analysis allows us to extract several psychological constructs underlying attitudinal statements on various benefits and drawbacks of WFH. Second, a latent-class cluster analysis (LCCA) helps us identify a few unobserved groups of workers in the sample whose characteristics are homogeneous within each group but heterogeneous across different groups. Third, in a similar vein, two latent-class choice models (LCCM) enable us to find a few distinctive forms of preferences for/against WFH adoption, separately for the present and near-future expectation, and explore possible reasons for such heterogeneous preferences. Also noteworthy is that we conduct unweighted analyses because our sampling frame is not clearly known.

4. RESULTS

4.1. *Attitudes on general items*

Table 2 presents six attitudinal constructs that we extracted from 18 statements (out of 31 statements in total) via principal axis factoring with the oblimin rotation. After selecting these statements based on their performance and relevance to travel behavior and WFH in previous surveys and studies (Kim et al., 2019; Lee et al., 2022; Matson et al., 2021), we asked them in a five-point Likert scale from strongly disagree to strongly agree. With R package *psych*, we computed factor scores based on the pattern matrices via the Bartlett score method.

TABLE 2. Attitudes on General Items and Statements with Loadings (N=816).

Attitudes	*Statements (Factor Loadings)*
Pro-car	• I like driving a car (0.897). • I definitely want to own a car (0.740). • To me, a car is just a way to get from place to place (-0.387).
Pro-transit-neighborhood	• I prefer to live close to transit, even if it means I'll have a smaller home and live in a more densely populated area (0.919). • I prefer to live in a spacious home, even if it is farther from public transportation or many places that I go to (-0.586).
Pro-waiting	• Having to wait is an annoying waste of time (-0.590). • My commute is a useful transition between home and work (or school) (0.516). • I wish I could instantly be at work (or school) – the trip itself is a waste of time (-0.506). • Having to wait can be a useful pause in a busy day (0.451).
Pro-exercise	• I like walking (0.565). • Getting regular exercise is very important to me (0.454). • I am committed to an environmentally-friendly lifestyle (0.413).
Pro-technology	• I like to be among the first to have the latest technology (0.474). • I would/do enjoy having a lot of luxury things (0.452). • Having internet connectivity everywhere I go is important to me (0.390).
Life-satisfied	• I am generally satisfied with my life (0.499). • I am too busy to do many of the things I like to do (-0.484). • Sharing my personal information or location via internet-enabled devices concerns me a lot (0.356).

Notes: The Kaiser-Meyer-Olkin (KMO) test for sampling adequacy returned 0.622 for 18 statements overall (i.e., mediocre), and the Bartlett's test of sphericity was significant at an alpha level of .05 ($\chi^2(153) = 2127$, $p < 0.001$). We chose principal axis factoring with the oblimin rotation and computed factor scores with the pattern matrix of a rotated solution via the Bartlett score method (Cumulative variance accounted for 0.36, the root mean square of the residuals or RMSR 0.02, Tucker Lewis Index of factoring reliability 0.892, and the root mean square error of approximation or RMSEA 0.041).

4.2. *Attitudes towards WFH*

To more thoroughly understand workers' attitudes towards WFH, we factor-analyzed their answers to another set of 20 attitudinal statements on a 5-point Likert scale from strongly disagree to strongly agree. By referring to previous surveys and relevant studies (de Haas et al., 2020; Matson et al., 2021; A. H. K. Wong et al., 2020), we developed these statements to capture perceived benefits and drawbacks of WFH. With an exploratory factor analysis with an oblique rotation, we identified five attitudinal constructs out of 15 statements, after excluding five statements only with minimal loadings (i.e., highest loadings on any factors below 0.25). Table 3 presents the pattern matrix of these 15 statements and five factors, and we suppressed loadings smaller than 0.25 for brevity. We name factors after the statement with the highest loading on each of them. "*Distracted-while-WFH*" represents difficulty in concentrating on work while WFH; "*Under-control-at-home*" refers to (perceived) increases in performance via WFH; "*Virtual-meeting-is-effective*" indicates the extent to which videoconferencing works as an effective alternative to in-person meetings; "*Firm-is-supportive*" captures the quality of support from an individual's company or direct supervisor; and "*Technology-fails-at-home*" refers to a negative experience because of technical problems while WFH.

TABLE 3. Exploratory Factor Analysis on Statements about Working from Home (N=816).

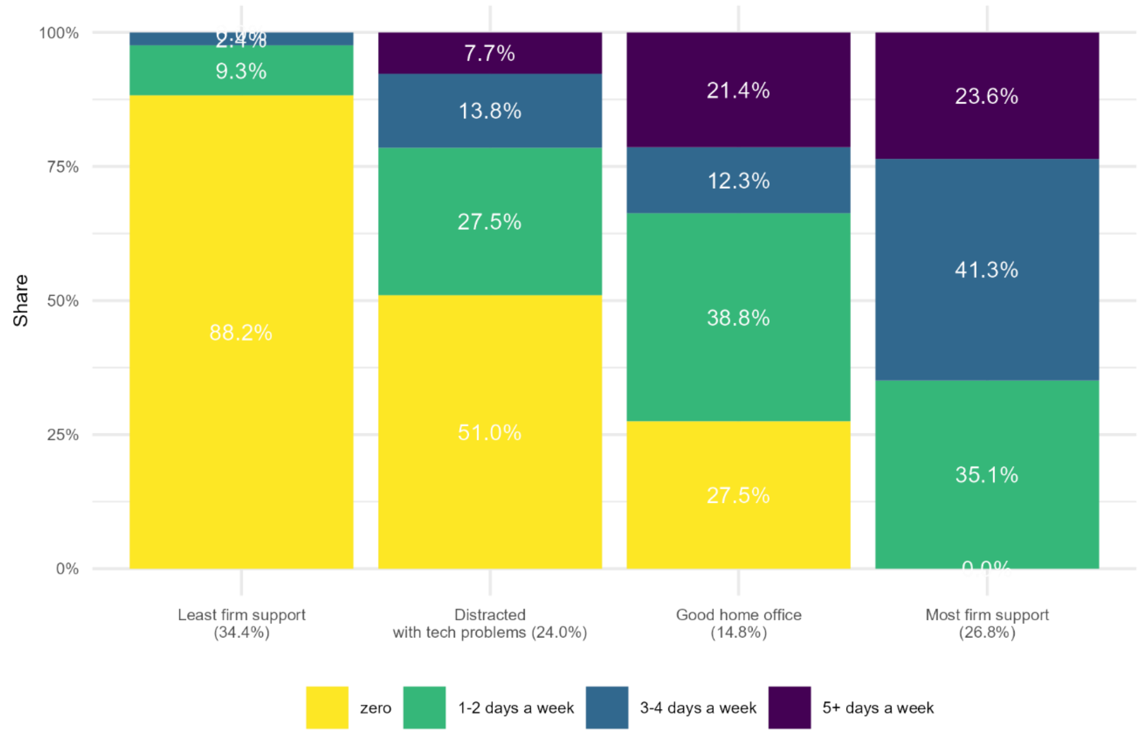
Statement	*Distracted-while-WFH*	*Under-control-at-home*	*Virtual-meeting-is-effective*	*Firm-is-supportive*	*Technology-fails-at-home*	*KMO value*
At home, I am easily disturbed by family members, children or others who live together during work.	0.503					0.887
Working from home makes me less disciplined/self-controlled.	0.654					0.854
At home, I am easily distracted by household chores during work.	0.763					0.845
I like the flexibility to decide when and where to do my work.		0.589				0.826
Working from home helps avoid unwanted distractions/interruptions often taking place in the workplace.		0.581				0.851
I find my productivity with online meetings to be similar to or even better than that with in-person meetings.			1.005			0.789
I experience good support from my employer to work from home				0.993		0.642
Learning how to use new technologies is often frustrating (e.g., software updates of online meeting/collaboration tools).					0.502	0.813
While working from home, technologies do not always work properly (e.g., spotty internet during online meetings).					0.532	0.853
The quality of interactions during online meetings is disappointing.			-0.321		0.277	0.780
I experience substantial gains in efficiency when working from home.	-0.423	0.414				0.838
Working from home helps me save on large expenses (e.g. commuting and parking).		0.460				0.842
At home, I have office hardware for working from home (e.g., desktop/laptop, camera, headset, printer).					-0.256	0.841
While working from home, it is difficult to draw a boundary between my work and my personal life.	0.400					0.908
The nature of my job requires me to physically go to work even during the pandemic.				-0.340		0.651

Notes: The Kaiser-Meyer-Olkin (KMO) test for sampling adequacy returned 0.833 for 15 statements overall (i.e., meritorious), and the Bartlett's test of sphericity was significant at an alpha level of .05 ($\chi^2(105) = 2308$, $p < 0.001$). We chose principal axis factoring with the oblimin rotation and computed factor scores with the pattern matrix of a rotated solution via the Bartlett score method (Cumulative variance accounted for 0.43, the root mean square of the residuals or RMSR 0.02, Tucker Lewis Index of factoring reliability 0.98, and the root mean square error of approximation or RMSEA 0.023). We employed R package *psych*, and loadings smaller than 0.25 are suppressed for brevity.

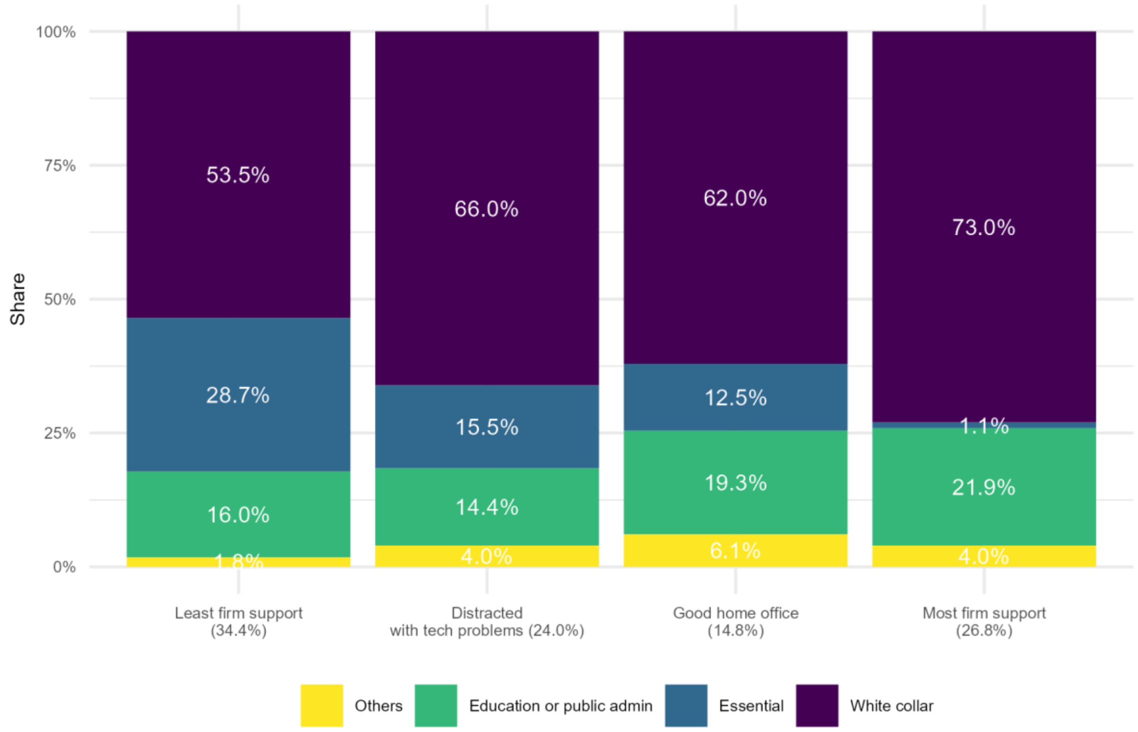
4.3. *Latent-Class Cluster Analysis (LCCA)*

In the latent-class cluster analysis, we identify four unobserved groups in the sample, each of which presents distinctive patterns of WFH frequency in December 2020, nature of job, and attitudes towards WFH (i.e., these variables are used as indicators in LCCA). We choose the four-class solution based on goodness-of-fit measures and interpretability (see Table A1). Below, we describe each class from the least to the most frequent WFH at the time of the survey administration (see Figure 2, panels (A) to (C)). In addition, we explain the profile of each class by examining class-specific summary statistics on the socioeconomics, demographics, household/housing characteristics, land-use attributes, and general attitudes of individuals (see Table A2). We create these summary statistics by weighting individual cases by the probabilities of belonging to latent classes. Note that all covariates are inactive; that is, they do not affect these probabilities but help identify the distinctive profile of each class after the estimation of LCCA.

(A) Working from Home in December 2020



(B) Nature of Jobs



1

(C) Attitudes towards WFH

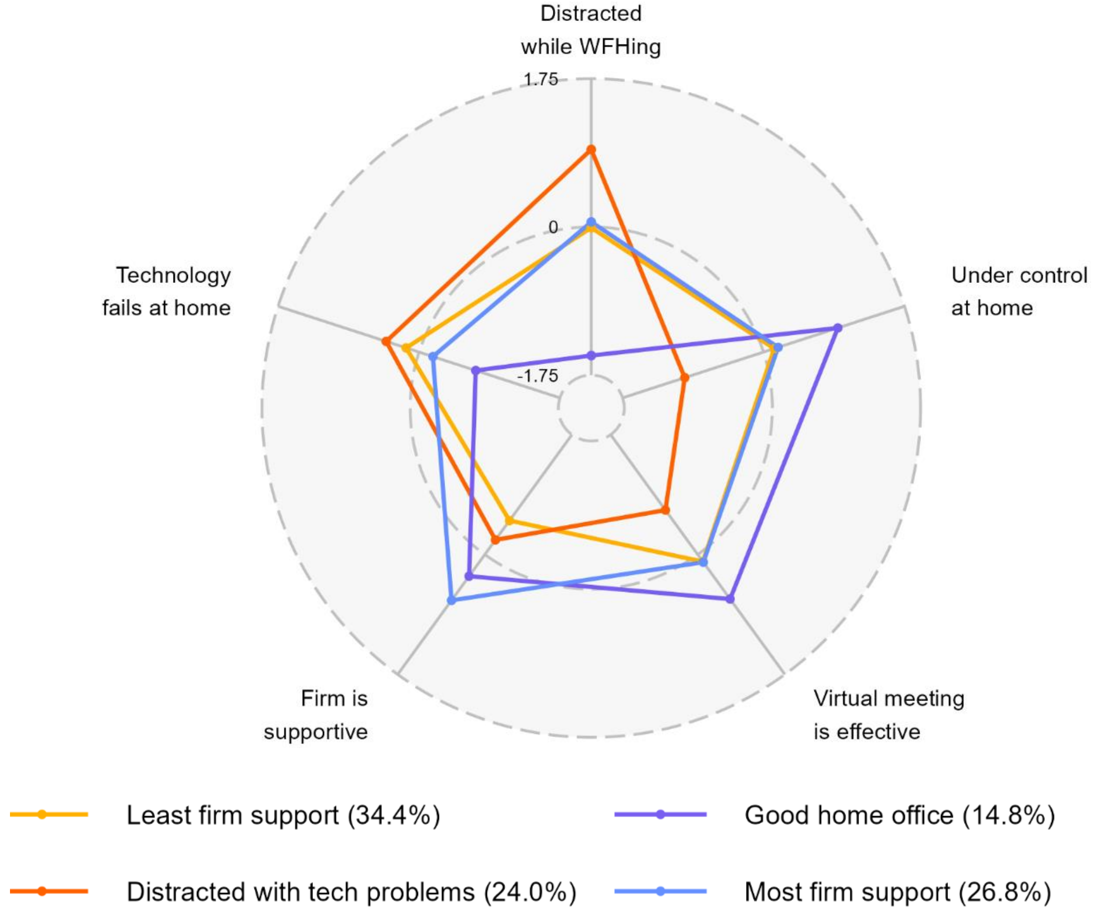


FIGURE 2. Latent-Class Cluster Analysis on WFH Frequency, Job Nature, and Attitudes (N=786).

Least firm support (34.4%): With regard to the attitudes towards WFH, the mean values are close to zero, except *Firm-is-supportive*, which is the lowest (-0.496) among the four classes. About a half of this class (53.5%) work at essential jobs, which, by definition, require one to report to work even under serious public health threats. Figure 2 (A) shows that 88.2% of this class do not work from home at all, and 9.3% of this class work remotely 1-2 days a week with smaller portions of them WFH more often. In brief, those in this class infrequently work from home at the moment of filling out the survey with sample-average attitudes towards WFH, and not surprisingly, their employers do not provide sufficient support for WFH. Note that members of this class tend to be less educated and less wealthy than those in the other classes (see Table A2), and some of them have work/study arrangements that are relatively unconducive to WFH. For instance, they work part time or study full time in part because they are young and have not yet finished their education.

Distracted with tech problems (24.0%): Because of distractions by others at home or by themselves (i.e., lack of self-discipline), many in this class undergo difficulty while WFH. Unfortunately, they neither experience efficiency gains nor find videoconferencing very effective. Instead, they receive less support from their employers and at times have technical issues while WFH. Interestingly, two thirds of this class work at white-collar jobs, and about half of them WFH non-zero days a week. That is, members of this class work from home to some extent, either by choice or by mandate; however, they find it quite challenging to work at their residences with distractions, less support from the employer, and non-trivial technical issues. Note that among the members of the four classes, those in this class live with the most children under 18, but not all of them appear to receive support from a domestic helper(s). In addition, they live in relatively small houses in part because most of them (79.5%) live in dense parts of Hong Kong, where housing is expensive. In short, members of this class live in challenging living arrangements before (or in relation to) the pandemic, which in part explains their struggle with WFH.

Good home office (14.8%): Overall, this class holds most positive (i.e., least negative) attitudes towards WFH, except on *Firm is supportive*. Compared to *Distracted with tech problems*, members of this class report more support from their employers (e.g., 0.316 vs. -0.214). Government policies appear to account for their relatively positive perception: i.e., this class consists of a large portion of teachers/government employees (19.3%), many of whom were asked to work from home, starting from the late November 2020. Note that members of *Good home office* are the most educated, are the wealthiest, and live the most in those houses larger than 700 sqft in the sample, in part because their households are mostly in later stages in life (e.g., on average, fewer children but more adults between 18 and 64 in the household than those in the other classes) and live in faraway suburbs or rural villages in New Territory. In sum, members of this class are better off than those of the other classes with the highest life satisfaction on average.

Most firm support (26.8%): Overall, among the four, this class reports the highest WFH frequency and holds the highest factor scores on *Firm is supportive*. When compared to *Distracted with tech problems*, this class displays the opposite attitudes (see Figure 2, panel (C)). Without much distractions at home, they experience decent efficiency gains while WFH, they find online meetings work equally well as in-person meetings, and they are less likely to report technical problems while WFH.

In sum, the cluster analysis indicates that attitudes, nature of job, and the current WFH frequency are closely associated with one other. Moreover, as for the adoption of WFH, support from one's firm/supervisor may be as important as attitudes towards WFH. For instance, members of *Distracted with tech problems* report technical difficulties while WFH and low confidence on employing technology. Still, about a half of this class participate in WFH. After all, some class members such as teachers or government employees were required to do WFH when the local infection wave hit Hong Kong in December 2020.

4.4. *Expected WFH by Latent Class*

With the LCCA results from Section 4.3, we now focus on future WFH (as an inactive covariate). Together with job nature, support from one's employer accounts for individuals' near-future expectation. To be specific, about a half of those in *Least firm support* select *About the same*, likely because they consist of the largest share in essential workers (28.7%) with the least support from employers (e.g., *Firm is supportive* -0.496). In the meantime, the middle two classes in Figure 3, *Distracted with tech problems* and *Good home office*, present quite comparable response patterns in their near-future expectations; however, at the moment the latter adopted WFH more often than the former. In fact, the former consists of a smaller share of teachers and government employees (mandated to work from home in December 2020) with a lower average factor score on *Firm-is-supportive* than the latter. Last but most importantly, the last class, *Most firm support*, presents the largest portion of increases in WFH among four classes: their responses are evenly distributed across more often (33.4% = 5.5% + 27.9%), about the same (32.1%), and less often (34.5 % = 24.7% + 9.8%). Note that members of this class are *slightly* more positive on WFH than the sample average (e.g., *Distracted-while-WFH* 0.059; *Virtual-meeting-is-effective* 0.112), but they receive (or perceive) substantially more support from the employer (e.g., *Firm-is-supportive* 0.669).

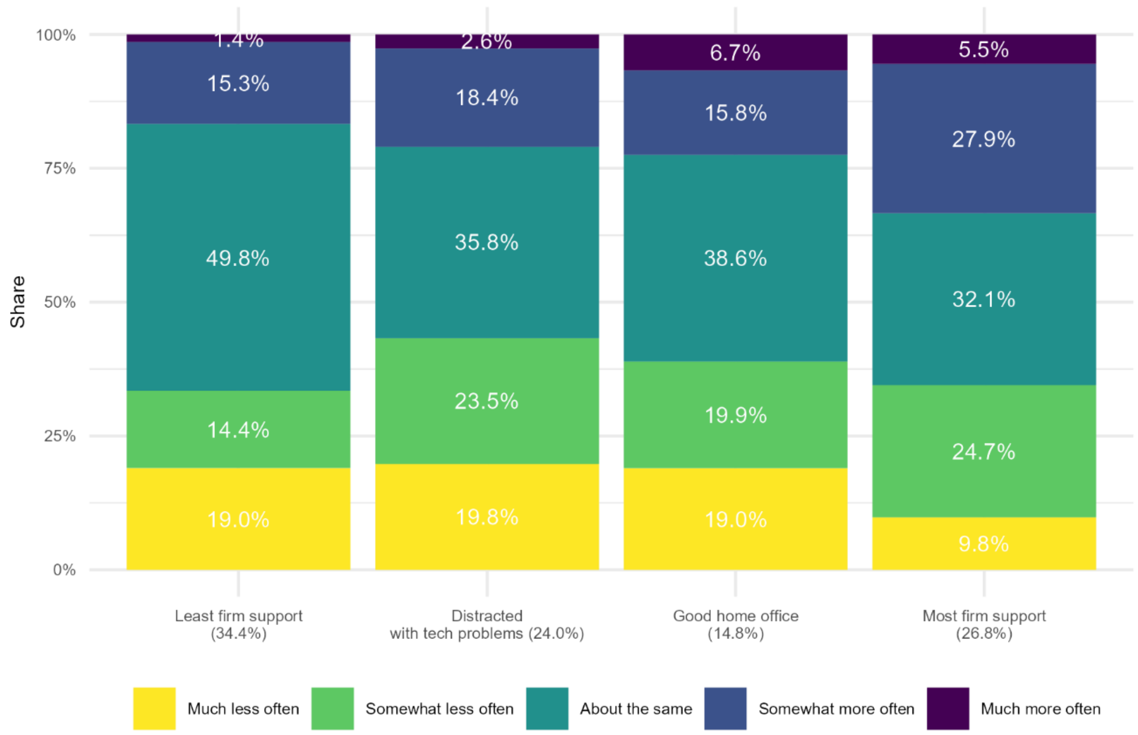


FIGURE 3. Expected WFH in April 2021 (Compared to that in December 2020) (N=786).

4.5. *Regression on the Present WFH*

We investigate various factors that account for the adoption/frequency of WFH at the time of the survey administration (December 2020). In doing so, we estimate an LCCM that captures heterogeneous preferences towards WFH, unique to each of unobserved groups in the sample. Note that the LCCM simultaneously determines individuals' characteristics accounting for their class membership, which allow us to identify underlying reasons behind the heterogeneous preferences. As regards the dependent variable in the choice model, we recode a count variable, the typical number of days per week WFH in the past 30 days (from zero to seven), to a four-level ordinal variable: zero days/week, 1-2 days/week, 3-4 days/week, and 5 or more days/week. As for the explanatory variables in the choice model, we test past WFH frequency (i.e., those in early phases of the pandemic), job characteristics (e.g., nature of job, commute time, and primary means of transportation), and residential districts. The dependent variable in the membership model is a latent categorical variable indicating individual's class membership. As regards the independent variables in the membership model, we employ attitudes towards WFH, general attitudes, and personal/household socioeconomics and demographics (see Table 3).

Table 4 presents the final results of the LCCM, in which three classes are named based on unique preferences. We refer to Table A3 for goodness-of-fit measures under varying numbers of latent classes. Since each class-specific choice model has a scale parameter, distinct from those of the others, a direct comparison of the magnitude of coefficients across latent classes is not meaningful. Thus, Table 4 includes "normalized" coefficients, original coefficients divided by that of *ln*(commute+1) separately for each class, which help the reader see the relative magnitude of various factors, in comparison to that of usual commute time.

Members of the "*Do it now because I did it recently*" class (61.4%) adopt WFH more now if they did so more in the past. To be specific, in terms of the magnitude of effects, adoption in the recent past (e.g., July-September 2020) accounts for the present WFH more than that in the remote past (e.g., before July 2020). Counterintuitively, commute time is negatively associated with the present frequency level of WFH, not aligned with previous studies (Helminen & Ristimäki, 2007; Loo & Wang, 2018; Mokhtarian et al., 2004; Singh et al., 2013). We speculate that with the other factors accounted for, those with longer commutes might have been those whose jobs were less suitable for remote work. By contrast, one's residential region appears to affect WFH frequency in an expected direction in larger magnitude than that of the commute time, for instance, by the factor of 10 for those living in New Territory, consisting of many exurbs and rural villages, compared to the Hong Kong Island, the densest and busiest region.

The current WFH frequency of the "*Tried a bit, but it didn't work out*" class (23.7%) is affected marginally (in magnitude) by WFH adoption for July-September 2020, but not by their experience before July 2020. In fact, the majority of this class (75.6%; refer to Table A4) didn't engage in WFH before July 2020, when remote work was recommended as an NPI measure but not mandated, except for those in education and public services. Interestingly, limited adoption for July-September 2020 (i.e., 1-2 days/week) appears to have led to less adoption in December 2020, suggesting that in such cases, employers found WFH not so much beneficial as damaging, or employees experienced more drawbacks than merits.

The smallest class (14.9%), "*It is okay unless too much*", presents preferences shaped more by older-period adoption (i.e., before July 2020), than by recent-past adoption (i.e., for July-September 2020). Interestingly, the recent adoption is associated negatively with the current WFH frequency, while the older-period adoption is associated positively. Members of this class may have selected "right" levels of WFH before July 2020, for which the infection trend in Hong Kong was not serious and the government mandated WFH sparingly (i.e., only for specific industries). However, for July-September 2020, when the government implemented mass-scale NPI measures (including remote work mandate), some members (especially those with zero days/week before July 2020; see Figure A1) may have adopted too high levels of WFH, not appropriate for the nature of their job, the residential environment, or preferences. For this reason, these members may have chosen lower frequencies of WFH in December 2020, compared to those for July-September 2020. In brief, for this class, adoption in the early phase (considered and selected carefully) accounts for the current adoption more (in magnitude) than adoption in the later phase (mandated by the government).

In Table 4, results from the membership model enable us to identify potential factors underlying heterogeneous preferences in the sample. If respondents are college-educated, compared to not having a bachelor's degree, they are more likely to belong to *Tried a bit, but it didn't work out* and *It is okay unless too much* than to *Do it now because I did it recently*. Note that members of the *It is okay unless too much* class present the highest adoption rates at three timepoints with the highest share of white-collar workers, both of which appear to be associated with college education. By contrast, those in *Tried a bit, but it didn't work out* record the least adoption rates at three timepoints with the largest proportion of essential workers. Members of this class may work on jobs that require both college education and on-site performance including those in the healthcare industry. In the meantime, two attitudes are found statistically significant in assigning individuals to distinct latent classes, i.e., *Firm is supportive* and *pro-technology*. Those with good support from the employer are most likely found among *It is okay unless too much* and least likely among *Tried a bit, but it didn't work out*. In addition, those who are less technologically savvy tend to belong to *Tried a bit, but it didn't work out*, in part because they could not adapt to remote-work practice as much as tech-savvier individuals did.

TABLE 4. Latent-Class Choice Model of WFH frequency in December 2020 (N=745).

Class name (share)	*Do it now because I did it recently.* (61.4%)			*Tried a bit, but it didn't work out.* (23.7%)			*It is okay unless too much.* (14.9%)		
Choice model (ordered logit)	*Estimate*	*normalized*	*sig.*	*estimate*	*normalized*	*sig.*	*estimate*	*normalized*	*sig.*
Telework for July-September 2020 (reference: zero days/week)									
1-2 days/week	5.77	34.32	***	-2643.99	-2.47	***	-2.61	-1.07	**
3-4 days/week	7.84	46.69	***	1267.06	1.18	***	-1.77	-0.73	**
5+ days/week	14.03	83.52	***	-1383.91	-1.29		-6.61	-2.71	***
Telework before July 2020 (reference: zero days/week)									
1-2 days/week	-0.56	-3.35	**	3189.53	2.97		-0.43	-0.17	
3-4 days/week	1.44	8.54	**	1834.79	1.71		4.16	1.71	***
5+ days/week	1.63	9.70	**	5082.70	4.74		13.49	5.53	***
Full-time worker (reference: no)									
Yes	0.32	1.92		23.68	0.02	***	-1.12	-0.46	**
Nature of job (reference: white-collar)									
Essential	-0.32	-1.90		-4422.66	-4.12		-0.02	-0.01	
Education/government	0.70	4.17	**	-3978.65	-3.71		0.76	0.31	**
Others	1.04	6.21	**	-23.21	-0.02		-13.39	-5.49	***
ln(commute time in minutes +1)	-0.17	-1.00	**	-1072.20	-1.00		-2.44	-1.00	***
Region of residence (reference: Hong Kong Island)									
Kowloon	0.90	5.36	**	3165.81	2.95		-1.05	-0.43	**
New Territory	1.68	10.01	***	211.32	0.20		0.26	0.11	
Thresholds									
1-2 days/week	3.73	22.17	***	-492.15	-0.46	***	-51.06	-20.95	
3-4 days/week	8.63	51.34	***	-357.96	-0.33		-12.52	-5.14	***
5+days/week	13.75	81.86	***	3658.30	3.41		-10.15	-4.17	***
Membership model (multinomial logit)				*estimate*		*sig.*	*estimate*		*sig.*
Intercepts				-1.53		***	-2.25		***
Educational attainment (reference: less than bachelor's)									
Bachelor's degree				0.69		**	0.69		**
Graduate degree				0.19			0.19		
Attitude									
Firm is supportive				-0.55		***	1.03		***
Pro-technology				-0.47		***			

Notes: Goodness of fit measures log likelihood: -551.645, AIC 1,213.290, BIC 1,467.027, and sample-size adjusted BIC 1,292.381. The normalized estimates are computed as the raw estimates divided by that of the log-transformed commute time, separately for each latent class. *** indicates that estimates are significant at the 99% confidence level; ** at the 95% level, and * at the 90% level.

4.6. *Regression on a Near-Future WFH*

We examine factors accounting for a near-future WFH in April 2021, a few months from the time of the survey administration in December 2020. In doing so, we model heterogeneous preferences by estimating an LCCM on expected frequency of WFH, compared to the current level: much less often, somewhat less often, about the same, somewhat more often, or much more often. We find that, consistent with LCCA results in section 4.4., current WFH frequency, nature of job, and *Firm is supportive* are associated with expected WFH frequency in the near future. Table 5 presents the final results of its choice model (ordered logit) and membership model (multinomial logit). Table 5 also includes normalized coefficients, raw estimates divided by that of the commute time (separately for each class), which help the reader assess relative importance (in magnitude) of various factors.

The largest class, "*Tried a bit, but prefer going back*" (58.3%), presents a mostly negative expectation related to the current and recent-past experience of WFH, i.e., the more often members of this class did/do WFH, the less likely they would continue doing so in a few months (one exception is those with the highest frequency for July-September 2020, 5 ore more days/week). For this class, moderate frequencies of WFH may indicate that their job is not very suitable for WFH in the first place or many members not valuing WFH very positive. In the meantime, the longer respondents' usual commutes were at the moment, the more frequently they would expect to engage in WFH in April 2021, likely to avoid disutility from those burdensome trips.

Members of the "*Building new normalcy around WFH*" class (22.6%) report expectations quite the opposite to those by the preceding class. Except for those with moderate frequencies in December 2020, 1-2 days/week, members with past/current adoption expect more frequent WFH in a near future than their past/current levels. Interestingly, their expectation is more associated (in magnitude) with the recent-past adoption (for July-

September 2020) than with the current adoption (in December 2020). Possible reasons include: (1) members may see a serious local infection wave would come in the following months (see Figure 2 for local trends) and be mentally prepared for similar adoption levels during the previous wave (for July-September 2020), or (2) continued adoption (for July-September 2020 and in December 2020) may have them accept WFH positively (e.g., for reduction in cognitive dissonance).

When predicting a near-future adoption, those in the "*Planning on a short-term horizon*" class (19.1%) are responsive positively to their present adoption (in December 2020), but they are not as much to their past adoption (for July-September 2020). In addition, class-specific probability-weighted summary statistics (see Table A6) reveal that their adoption rates at three timepoints were the lowest among all classes, and their share in white-collar workers is the smallest and their share in essential workers is the largest. These patterns suggest that members of this class adopt WFH mostly by government mandate or company policy at the moment, but less likely by their own choice/preference.

Results from the membership model in Table 5 provide valuable insights into primary reasons behind heterogeneous preferences towards a near-future WFH: one's residential environment, perceived/actual support for WFH by the employer, and subjective prediction of the end of the pandemic. If respondents live in a mid-sized housing unit, between 301 and 500 square feet, they are more likely to belong to the largest class, *Tried a bit, but prefer going back*, than to the other classes. In comparison, class-specific summary statistics (see Table A6) present that *Building new normalcy around WFH* have the largest share residing in a house larger than 700 sqft, and *Planning on a short-term horizon* have the largest share living in a house under 301 sqft. These patterns are consistent with recent findings that the quality of home office is critical in one's (continued) adoption of WFH (Baruch, 2000; Cuerdo-Vilches et al., 2021; Sifri et al., 2022). In addition, varying levels of employers' support have individuals hold distinct preferences. Those with less support are likely to be found among *Planning on a short-term horizon*, and on average, members of the *Building new normalcy around WFH* class report the highest factor score on *Firm is supportive* (see Table A6). Last but most importantly, those who predict the pandemic would end sooner (i.e., in six months from December 2020) than later (i.e., more than six months) are likely to belong to *Planning on a short-term horizon*, whose members appear not to make changes in work arrangement with a longer-term perspective. By contrast, the *Building new normalcy around WFH* class consists of the largest share choosing "*Two years or longer*", consistent with their expectation in continuing hybrid work arrangement.

TABLE 5. Latent-Class Choice model of WFH frequency in April 2021, relative to WFH frequency in December 2020 (N=755).

Class name (share)	*Tried a bit, but prefer going back. (58.3%)*			*Building new normalcy around WFH. (22.6%)*			*Planning on a short-term horizon. (19.1%)*		
Choice model (ordered logit)	*estimate*	*normalized*	*sig.*	*estimate*	*normalized*	*sig.*	*estimate*	*normalized*	*sig.*
Telework in December 2020 (reference: zero days/week)									
1-2 days/week	-0.66	-2.07	**	-1165.24	-17.39	***	1445.72	0.52	***
3-4 days/week	0.08	0.25		442.61	6.60	***	3308.28	1.20	***
5+ days/week	0.18	0.56		478.39	7.14	***	6339.46	2.29	***
Telework for July-September 2020 (reference: zero days/week)									
1-2 days/week	-0.88	-2.77	**	2351.85	35.09	***	2148.17	0.78	***
3-4 days/week	-0.61	-1.92	**	2050.66	30.60	***	-4379.35	-1.58	
5+ days/week	2.12	6.63	***	-1134.20	-16.92		-7323.55	-2.65	
Full-time worker (reference: no)									
Yes	-0.70	-2.20	**	885.80	13.22	***	-2229.90	-0.81	***
Nature of job (reference: white-collar)									
Essential	-0.14	-0.45		381.28	5.69	***	-1092.29	-0.40	***
Education/government	0.60	1.87	**	-752.07	-11.22	***	-2108.73	-0.76	***
Others	0.14	0.44		1660.59	24.78		-6652.46	-2.41	
ln(commute time in minutes +1)	0.32	1.00	**	-67.02	-1.00	***	-2763.98	-1.00	***
Region of residence (reference: Hong Kong Island)									
Kowloon	-0.62	-1.94	**	-374.06	-5.58	***	1071.68	0.39	***
New Territory	-0.66	-2.07	**	356.84	5.32		121.23	0.04	
Thresholds									
Somewhat less often	-3.21	-10.05	***	-2942.87	-43.91		-9892.48	-3.58	
About the same	-1.21	-3.79	**	244.73	3.65	***	-9526.66	-3.45	
Somewhat more often	1.80	5.63	***	1445.63	21.57		-8129.29	-2.94	
Much more often	4.28	13.42	***	3460.86	51.64		-3223.39	-1.17	
Membership model (multinomial logit)				*estimate*		*sig.*	*estimate*		*sig.*
Intercepts				-0.17			-0.05		
Size of home (reference: less than 301sqft)									
301-500 sqft				-0.51		**	-0.51		**
501-700 sqft				-0.31			-0.31		
Larger than 700 sqft				-0.07			-0.07		
Attitude									
Firm is supportive				0.13			-0.39		***
When will the pandemic be over? (reference: in six months)									
In a year				-0.80		**	-0.68		**
In a year and half				-0.53			-0.93		**
In two years or longer				-0.31			-1.66		***

Notes: Goodness of fit measures log likelihood: -931.920, AIC 1,991.840, BIC 2,287.950, and sample-size adjusted BIC 2,084.724. The normalized estimates are computed as the raw estimates divided by that of the log-transformed commute time, separately for each latent class. *** indicates that estimates are significant at the 99% confidence level; ** at the 95% level, and * at the 90% level.

5. DISCUSSION

This study examined various factors including perceptions and preferences, which account for WFH during the COVID-19 pandemic and expected WFH a few months later, in Hong Kong. First, we explored respondents' attitudes towards various aspects of WFH. The exploratory factor analysis uncovered two competing perspectives on WFH in the sample, one focusing on its merits and the other on its drawbacks. Note that, in most cases under the pandemic, WFH is not an arrangement adopted by choice or well thought of/planned in advance, but instead, mandated for health concerns. Thus, many workers were likely to be assigned to remote work without an understanding of and support for best practices, proper expectations, or standard protocols about commonly occurring situations. For these reasons, it would be crucial to the success of WFH that employers and employees engage in a collective effort to discuss problems, search for solutions, and improve productivity, instead of giving and receiving a one-size-fits-all one-way direction (culturally more common in Asia than in Western countries).

To identify distinctive (tele)commuting profiles in the sample, we performed a cluster analysis of the current frequency of WFH, attitudes towards WFH, and the nature of job as indicators. We identified four classes of workers: (1) those with sample-average attitudes and little employer support, (2) those struggling with distraction, insufficient support, and technology, (3) those with good home office and decent employer support, and (4) those with substantial employer support. These results suggest that positive attitudes towards WFH are often in line with the support workers receive for WFH and the frequency of WFH. In addition, those with positive WFH attitudes or employer support (e.g., members of the last two classes) expect to work from home more often in the future than those with negative attitudes or limited support (e.g., members of the first two classes).

To understand workers' choices of (expected) WFH frequencies at the moment and in a near future, we estimated two LCCMs, separately for each choice. We found that employer support was consistently statistically significant in current and future WFH adoption, but worker attitudes towards WFH were not. In Western society, choices are (presumably) made by individuals, which may explain the continued emphasis in the literature on individual attitudes towards WFH. By contrast, in hierarchical Asian society, where those in authorities are given more discretion than others (i.e., high power distance), decisions are made often by senior members of a group, and subordinates comply with these decisions (Himawan et al., 2022) . Thus, in Hong Kong and likely in other Asian countries as well, whether to continue WFH depends more on employer support.

Not surprisingly, the frequency of WFH at one timepoint affects it at later timepoints, consistent with findings in recent studies (Beck et al., 2020; Mouratidis & Peters, 2022; Nguyen, 2021). Those who have recently frequently worked remotely are likely to be those who were/are mandated to work from home (e.g., public school teachers), those whose jobs were/are still conducive to WFH (at least perceived so by the employer), those whose employers were/are still supportive, or those who found/find WFH to work well for themselves (likely in this order, given that WFH was not widely adopted in Hong Kong in the past).

The quality of home office is important to the continuation of WFH in a near future (Baruch, 2000; Cuerdo-Vilches et al., 2021; Shieh & Freestone, 2021). For those without sufficient residential space for remote work, the government may consider the provision of coworking space (e.g., in temporary operation during the pandemic), which would enable those individuals to avoid (some of) commute trips and reduce exposure to health risks. If they cannot engage in WFH because of the nature of their job (e.g. essential workers), the government may support companies to provide safe work environment, subsidize on expenses on safety measures at worksite, and prioritize frontline workers for health monitoring, diagnosis, and treatment. In addition, on a given day employers may adopt calling in only a subset of employees for on-site work, reducing maximum occupancy at the office (e.g., via hot desking), and support temporary relocation of residence to a remote place for better home office (e.g., parent/relative's home).

Healthcare professionals and government officials should support individuals to develop well-founded perspectives about near-future public-health situations, critical to those individuals' choices and decisions (in various time horizons) affecting wellbeing in various domains (e.g., finance and mental health) in coming months/years. For instance, members of *Building new normalcy around WFH* may make longer-term investment in home office, and those of *Planning on a short-term horizon* may lack resources to do so and be eager to return to pre-pandemic routines. Thus, the latter would get worse-off if the pandemic lasts too long, and the former would have valuable resources wasted if the threat to public health ends too soon. Unfortunately, given extreme uncertainty in behaviors of new variants, progress in new vaccines/treatment, and shifting perspectives and responses of diverse players in society, perfect prediction is not possible; however, at the minimum, public agencies and transportation professionals are advised to share latest relevant statistics, make the decision-making process open and transparent, and develop and update contingent plans for a range of possible near-future scenarios. These measures will help individuals reduce stress and confusion, take proactive/productive actions, and collectively identify better ways moving forward.

This study provides insights into the determinants of (future) WFH, which would help planners and policymakers promote it. However, the net benefits of WFH to society might not always be positive. For instance, congestion relief in peak hours (and associated reduction in fossil-fuel use, greenhouse gas emissions, and air pollution) and savings on infrastructure maintenance and capacity management could be cancelled out by subsequent rebound effects, such as increased demand for leisure travel or for remote residential locations (i.e., less frequent but substantially longer commutes by motorized modes). In this context, the government may select certain occupations, industries, or geographic areas (e.g., firms in the central business district that are more responsible for peak-hour traffic) with greater potential to benefit and support their efforts to build environments conducive to WFH. For instance, the Hong Kong government may consider helping IT industries geographically expand their search for and hiring of talent in remote places without incurring relocation costs and contributing to downtown traffic.

6. CONCLUSION

In this study, we examined individuals' motivations and determinants of WFH during and after the pandemic. In doing so, we analyzed attitudes towards WFH, the profiles of distinctive types of workers engaged in WFH, and the determinants of the current and future expected frequency of WFH among 816 workers in Hong Kong, recruited in December 2020 (i.e., during the fourth wave of local infections). Our results reveal that that the (future) frequency of WFH is affected by attitudes, the past frequency of WFH, and certain constraining/facilitating factors such as the nature of jobs, the support of employers, and the size of home. To promote continued WFH (at least partially) and manage concentrated demand on transportation systems during peak hours (and potentially reduce travel demand in general), planners and policymakers are advised to acknowledge the central role of employer support, target certain businesses, industries, or areas with a greater potential for reduction in travel demand, and consider polycentric regional development with suburban employment centers (e.g., for satellite offices).

This study has a few limitations, and in response, we propose directions for further research. First, because of survey recruitment via social media, our sample includes many young, tech-savvy, well-educated or wealthy individuals, while not representing the general public in Hong Kong. Thus, researchers need to consider other recruitment methods (e.g., random address-based sampling), which enable them to build a representative sample. Second, we classified individuals' jobs into four broad categories, which may have failed to capture important but more nuanced differences among those occupations that differ from one another at the low level. In this sense, future research requires to incorporate more details on individuals' job into their analysis: e.g., the extent to which the nature of job allows WFH, employers support WFH, and individuals prefer WFH. Note also that we examined the role of early-phase WFH adoption, but not pre-pandemic adoption, because of a flaw in survey design. Hence, future studies need be more rigorous by collecting and accounting for pre-pandemic behavior like Figure 1 suggests. Third, as the pandemic progresses in unpredictable manners, we need follow-up data collection and investigation to track longitudinal changes in the effects of various constraining/facilitating factors on WFH (e.g., fatigue from prolonged mobility restriction, investment in home offices, and relationship crisis in the household). Last but most importantly, we analyzed WFH among workers in Hong Kong, and future studies on other parts of the world will allow to determine common or distinct relationships between WFH and related factors and identify sources of such variations (e.g., culture, political systems, and policy responses).

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AUTHOR CONTRIBUTION

The authors confirm contribution to the paper as follows: study conception and model design: Lee, De Vos; data collection and processing: Lee; analysis and interpretation of results: Lee, De Vos; draft manuscript preparation: Lee, De Vos. All authors reviewed the results and approved the final version of the manuscript.

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TABLE A1 Goodness-of-fit Measures by the Number of Latent Classes (N=786).

Number of classes	Number of parameters	Log-likelihood	AIC	BIC	Sample-size-adjusted BIC	Class size Class 1	Class 2	Class 3	Class 4	Class 5
2	28	-7,350.210	14,732.419	14,807.090	14,756.282	64.7%	35.3%			
3	40	-7,170.584	14,397.168	14,527.843	14,438.928	42.5%	29.2%	28.3%		
4	52	-7,096.248	14,272.497	14,459.175	14,332.155	34.4%	26.8%	24.0%	14.8%	
5	64	-7,039.091	14,182.182	14,424.864	14,259.738	35.4%	23.2%	16.9%	12.3%	12.2%

Notes: For the last five columns, the size of latent classes are in the descending order (i.e., the largest comes in the first among the five columns. For the sample-size-adjusted BIC, (n+2)/24 was used instead of n (i.e., sample size). These statistics were computed via *M*plus 8.6.

TABLE A2 Probability-Weighted Class-Specific Summary Statistics (N=786).

Variable	Least firm support	Distracted with tech problems	Good home office	Most firm support
Share	**34.4%**	24.0%	*14.8%*	26.8%
Indicators				
Working from home in December 2020				
zero	**88.2%**	51.0%	27.5%	*0.0%*
1-2 days a week	*9.3%*	27.5%	**38.8%**	35.1%
3-4 days a week	*2.4%*	13.8%	12.3%	**41.3%**
5+ days a week	*0.0%*	7.7%	21.4%	**23.6%**
Nature of job				
White-collar	*53.5%*	66.0%	62.0%	**73.0%**
Essential	**28.7%**	15.5%	12.5%	*1.1%*
Government/education	16.0%	*14.4%*	19.3%	**21.9%**
Others	*1.8%*	4.0%	**6.1%**	4.0%
Attitudes on WFH				
Distracted while WFH	-0.009	**0.915**	*-1.519*	0.059
Under control at home	0.133	*-0.978*	**0.923**	0.181
Online meeting is effective	0.103	*-0.649*	**0.650**	0.112
Firm is supportive	*-0.496*	-0.214	0.316	**0.669**
Technology fails at home	0.160	**0.408**	*-0.704*	-0.172
Inactive covariates				
Working from home in April 2021 (compared to December 2020)				
Much less often	19.0%	**19.8%**	19.0%	*9.8%*
Somewhat less often	*14.4%*	23.5%	19.9%	**24.7%**
About the same	**49.8%**	35.8%	38.6%	*32.1%*
Somewhat more often	*15.3%*	18.4%	15.8%	**27.9%**
Much more often	*1.4%*	2.6%	**6.7%**	5.5%
Age group				
18-24	11.2%	*9.9%*	10.4%	**11.5%**
25-34	36.0%	*35.2%*	40.1%	**40.7%**
35-44	31.2%	*31.1%*	**33.1%**	33.0%
45-54	14.9%	**17.1%**	*11.9%*	13.1%
55+	**6.7%**	6.7%	4.5%	*1.8%*
Educational attainment				
Less than Bachelor's	**39.5%**	31.3%	*16.1%*	20.2%
Bachelor's	*44.2%*	46.7%	**54.7%**	52.2%
Postgraduate	*16.3%*	22.0%	**29.3%**	27.6%
Work arrangement				
Work full time	*83.0%*	84.4%	84.9%	**90.5%**
Work part time	**16.0%**	13.8%	14.3%	*8.6%*
Work at multiple jobs	4.8%	**6.1%**	5.6%	*2.8%*
Student status				
Study full time	**6.6%**	6.2%	*2.7%*	3.5%
Study part time	5.0%	**6.3%**	*4.1%*	4.2%
Average commute time (minute)	**36.189**	35.489	*25.843*	28.488
Primary commute mode				
Rail	**52.7%**	45.6%	*43.3%*	52.4%
Bus	37.2%	**44.9%**	42.9%	*36.1%*
Others	10.0%	*9.5%*	**13.8%**	11.5%

Variable	Least firm support	Distracted with tech problems	Good home office	Most firm support
Share	**34.4%**	24.0%	*14.8%*	26.8%
Household characteristics				
N(household)	3.448	**3.603**	*3.131*	3.362
N(under 18)	0.311	**0.403**	*0.220*	0.295
N(18-64)	2.633	**2.682**	*2.439*	2.573
N(65 or older)	0.433	0.472	*0.409*	**0.482**
Presence of domestic helper(s)	*8.9%*	**13.3%**	10.6%	11.1%
Monthly household income				
Under HK$20,000	**19.1%**	11.9%	12.1%	*11.0%*
HK$20,000 to HK$39,999	**34.4%**	36.0%	*28.5%*	31.7%
HK$40,000 to HK$59,999	*23.1%*	25.7%	**25.9%**	25.0%
HK$60,000 or more	*23.3%*	26.4%	**33.4%**	32.4%
Housing type				
Public housing	29.3%	28.0%	*17.2%*	**31.5%**
Home ownership scheme flat	*15.4%*	16.3%	**18.0%**	16.3%
Private housing estate	38.6%	**44.6%**	42.9%	*34.1%*
Tenement house (with a lift)	**10.4%**	*4.0%*	9.5%	7.5%
Tenement house (without a lift)	4.2%	*3.6%*	**4.8%**	5.5%
Village house	*2.2%*	3.6%	**7.5%**	5.0%
Housing size (square foot)				
Under 301	**21.2%**	19.8%	19.1%	*18.1%*
301-500	**37.4%**	37.3%	*32.3%*	34.8%
501-700	*28.7%*	30.3%	30.4%	**34.2%**
over 700	12.7%	*12.6%*	**18.1%**	12.9%
Housing tenure				
Rent	**41.1%**	38.5%	39.0%	*36.9%*
Own	44.6%	*44.5%*	47.7%	**47.9%**
Provided by someone else	14.3%	**17.0%**	*13.3%*	15.2%
Region of current residence				
Hong Kong Island	17.7%	**22.6%**	19.7%	*15.9%*
Kowloon	29.5%	29.7%	*27.2%*	**33.1%**
New Territories	52.8%	*47.6%*	**53.2%**	51.0%
Current neighborhood (self-reported)				
Urban	77.5%	**79.5%**	*74.0%*	78.4%
Suburban	13.7%	*11.4%*	**18.2%**	13.3%
Rural	8.8%	**9.1%**	*7.8%*	8.2%
Preferred neighborhood in the long run				
Urban	69.1%	**74.3%**	*66.6%*	72.6%
Suburban	**19.0%**	*16.4%*	25.8%	18.8%
Rural	**11.9%**	9.3%	*7.6%*	8.6%
General attitudes				
Pro-car	-0.021	*-0.029*	**0.045**	0.023
Pro-transit-neighborhood	*-0.055*	**0.064**	-0.011	0.011
Pro-waiting	**0.058**	0.037	*-0.156*	0.011
Pro-exercise	*-0.049*	-0.005	**0.100**	0.020
Pro-technology	0.033	-0.068	*-0.093*	**0.074**
Life-satisfied	-0.022	*-0.038*	**0.099**	0.015

Notes: Averages are computed for continuous variables, and shares are computed for discrete variables. The largest value in each row is **bolded**, and the smallest value in each row is *italicized and underlined*. All covariates are inactive: i.e., they do not affect the probabilities of individuals belonging to certain latent classes, but help identify the individual, household, land-use, and attitudinal profiles of each class.

TABLE A3 Goodness-of-fit Measures by the Number of Latent Classes (N=745).

Number of classes	Number of parameters	Log-likelihood	AIC	BIC	Sample-size-adjusted BIC	Class size				
						Class 1	Class 2	Class 3	Class 4	Class 5
2	27	- 553.290	1,160.579	1,282.477	1,196.749	58.9%	41.1%			
3	41	- 518.998	1,119.995	1,305.098	1,174.919	47.1%	30.7%	22.2%		
4	55	- 515.995	1,141.990	1,390.299	1,215.669	41.1%	22.2%	18.6%	18.1%	
5	69	- 509.610	1,157.220	1,468.736	1,249.654	39.3%	19.7%	18.8%	11.3%	10.9%

Notes: For the last five columns, the size of latent classes are in the descending order (i.e., the largest comes in the first among the five columns. For the sample-size-adjusted BIC, (n+2)/24 was used instead of n (i.e., sample size). These statistics were computed via *M*plus 8.6.

TABLE A4 Probability-Weighted Class-Specific Summary Statistics (N=745).

Variable	*Do it now because I did it recently.*	*Tried a bit, but it didn't work out.*	*It is okay unless too much.*
Share	**61.4%**	23.7%	*14.9%*
Choice outcome			
Working from home in December 2020			
Zero	42.8%	**85.3%**	*0.0%*
1-2 days a week	30.9%	*3.0%*	**35.3%**
3-4 days a week	18.0%	10.2%	**25.1%**
5+ days a week	8.4%	*1.5%*	**39.7%**
Covariates in the choice model			
Working from home for July-September 2020			
zero	43.7%	**48.7%**	*27.2%*
1-2 days a week	26.1%	*25.0%*	**35.5%**
3-4 days a week	20.7%	*16.2%*	**21.3%**
5+ days a week	*9.5%*	10.1%	**16.0%**
Working from home before July 2020			
zero	*69.3%*	**75.6%**	59.8%
1-2 days a week	17.6%	*13.2%*	**21.9%**
3-4 days a week	**8.0%**	*5.1%*	7.6%
5+ days a week	*5.1%*	6.1%	**10.7%**
Work arrangement			
Work full time	*85.1%*	86.2%	**89.7%**
Nature of job			
White-collar	*60.0%*	63.8%	**71.9%**
Essential	17.4%	**19.0%**	*3.5%*
Government/education	18.5%	*14.4%*	**20.6%**
Others	4.0%	*2.9%*	**4.1%**
Average commute time (minute)	**33.848**	32.415	*26.140*
Region of current residence			
Hong Kong Island	**18.7%**	17.7%	*15.6%*
Kowloon	*30.0%*	30.3%	**34.3%**
New Territories	51.3%	**52.0%**	*50.1%*
Covariates in the membership model			
Educational attainment			
Less than Bachelor's	32.9%	**25.8%**	*16.4%*
Bachelor's	*42.6%*	57.3%	**57.7%**
Postgraduate	24.6%	*16.9%*	**25.9%**
Attitudes on WFH			
Firm is supportive	-0.007	*-0.476*	**0.812**
General attitudes			
Pro-technology	**0.113**	*-0.340*	0.028
Inactive covariates			
Age group			
18-24	11.2%	*10.8%*	**12.8%**
25-34	*35.7%*	**41.3%**	39.1%
35-44	**34.2%**	*28.9%*	29.4%
45-54	*13.6%*	15.1%	**17.1%**
55+	**5.2%**	3.9%	*1.5%*
Work arrangement			
Work part time	**14.1%**	11.3%	*10.5%*

Variable	*Do it now because I did it recently.*	*Tried a bit, but it didn't work out.*	*It is okay unless too much.*
Share	**61.4%**	23.7%	*14.9%*
Work at multiple jobs	4.7%	**5.1%**	*3.9%*
Student status			
Study full time	5.4%	*4.7%*	**6.2%**
Study part time	4.8%	**7.0%**	*2.6%*
Primary commute mode			
Rail	50.3%	*46.0%*	**52.9%**
Bus	38.7%	**44.1%**	*35.3%*
Others	11.1%	*9.9%*	**11.8%**
Household characteristics			
N(household)	3.425	**3.456**	*3.328*
N(under 18)	0.314	**0.343**	*0.287*
N(18-64)	2.607	**2.628**	*2.553*
N(65 or older)	0.457	*0.413*	**0.462**
Presence of domestic helper(s)	**10.9%**	*9.9%*	10.7%
Monthly household income			
Under HK$20,000	14.0%	**17.0%**	*11.1%*
HK$20,000 to HK$39,999	**34.9%**	33.3%	*27.4%*
HK$40,000 to HK$59,999	*22.8%*	25.7%	**29.7%**
HK$60,000 or more	28.2%	*24.0%*	**31.8%**
Housing type			
Public housing	28.1%	**31.6%**	*25.4%*
Home ownership scheme flat	**17.8%**	15.9%	*14.0%*
Private housing estate	37.8%	*33.8%*	**48.1%**
Tenement house (with a lift)	7.2%	**8.0%**	*6.6%*
Tenement house (without a lift)	4.7%	**4.9%**	*3.3%*
Village house	4.4%	**5.7%**	*2.6%*
Housing size (square foot)			
Under 301	*19.1%*	20.7%	**20.9%**
301-500	36.1%	**38.8%**	*32.2%*
501-700	31.4%	*28.7%*	**34.1%**
over 700	**13.3%**	*11.9%*	12.8%
Housing tenure			
Rent	*38.9%*	**42.0%**	33.0%
Own	46.4%	*42.5%*	**49.3%**
Provided by someone else	*14.7%*	15.5%	**17.7%**
Current neighborhood (self-reported)			
Urban	77.4%	*76.1%*	**80.6%**
Suburban	13.3%	**15.1%**	*12.0%*
Rural	**9.3%**	8.8%	*7.5%*
Preferred neighborhood in the long run			
Urban	70.9%	*68.9%*	**73.5%**
Suburban	19.1%	*18.4%*	**19.2%**
Rural	10.0%	**12.7%**	*7.4%*
Attitudes on WFH			
Distracted while WFHing	**0.012**	-0.006	*-0.086*
Under control at home	0.013	*-0.012*	**0.054**
Online meeting is effective	*0.001*	0.014	**0.029**
Technology fails at home	**0.052**	0.006	*-0.276*
General attitudes			
Pro-car	**0.040**	*-0.141*	0.031
Pro-transit-neighborhood	0.023	*-0.145*	0.087
Pro-waiting	*-0.032*	0.070	**0.085**
Pro-exercise	**0.026**	*-0.033*	-0.004
Life-satisfied	-0.005	*-0.044*	**0.047**

Notes: Averages are computed for continuous variables, and shares are computed for discrete variables. The largest value in each row is **bolded**, and the smallest value in each row is *italicized and underlined*. All covariates are inactive: i.e., they do not affect the probabilities of individuals belonging to certain latent classes, but help identify the individual, household, land-use, and attitudinal profiles of each class.

TABLE A5 Goodness-of-fit Measures by the Number of Latent Classes (N=755).

Number of classes	Number of parameters	Log-likelihood	AIC	BIC	Sample-size-adjusted BIC	Class size Class 1	Class 2	Class 3	Class 4	Class 5
2	29	- 895.659	1,849.319	1,980.246	1,888.168	75.1%	24.9%			
3	44	- 859.633	1,807.266	2,005.914	1,866.210	57.5%	24.0%	18.5%		
4	57	- 870.530	1,855.059	2,112.398	1,931.418	34.3%	26.8%	23.8%	15.1%	
5	74	- 846.118	1,840.236	2,174.325	1,939.368	26.1%	23.9%	18.3%	18.0%	13.8%

Notes: For the last five columns, the size of latent classes are in the descending order (i.e., the largest comes in the first among the five columns. For the sample-size-adjusted BIC, (n+2)/24 was used instead of n (i.e., sample size). These statistics were computed via *M*plus 8.6.

TABLE A6 Probability-Weighted Class-Specific Summary Statistics (N=755).

Variable	*Tried a bit, but prefer going back.*	*Building new normalcy around WFH.*	*Planning on a short-term horizon.*
Share	**58.3%**	22.6%	*19.1%*
Choice outcome			
Working from home in April 2021 (compared to December 2020)			
Much less often	6.8%	*0.0%*	**67.4%**
Somewhat less often	**24.4%**	20.5%	*7.3%*
About the same	**53.2%**	34.4%	*9.8%*
Somewhat more often	13.4%	**38.1%**	*12.4%*
Much more often	2.2%	**7.0%**	*3.1%*
Covariates in the choice model			
Working from home in December 2020			
zero	44.9%	*42.7%*	**54.4%**
1-2 days a week	**25.8%**	25.7%	*22.5%*
3-4 days a week	17.2%	**19.7%**	*15.2%*
5+ days a week	**12.1%**	11.9%	*7.9%*
Working from home for July-September 2020			
zero	40.4%	*40.2%*	**48.9%**
1-2 days a week	**28.3%**	*24.2%*	27.3%
3-4 days a week	20.8%	**23.6%**	*14.6%*
5+ days a week	10.5%	**12.0%**	*9.2%*
Work arrangement			
Work full time	**87.4%**	*84.4%*	84.8%
Nature of job			
White-collar	**64.9%**	61.2%	*58.2%*
Essential	14.7%	15.6%	**19.1%**
Government/education	*16.6%*	**20.0%**	19.2%
Others	**3.7%**	*3.2%*	3.5%
Average commute time (minute)	**32.650**	*31.105*	32.049
Region of current residence			
Hong Kong Island	18.0%	*18.0%*	**21.4%**
Kowloon	**31.3%**	*28.7%*	31.3%
New Territories	50.6%	**53.3%**	*47.4%*
Covariates in the membership model			
Housing size (square foot)			
Under 301	*17.2%*	20.6%	**27.2%**
301-500	**39.5%**	32.0%	*30.8%*
501-700	31.2%	**31.6%**	*28.2%*
over 700	*12.1%*	**15.8%**	13.8%
Attitudes on WFH			
Firm is supportive	0.047	**0.181**	*-0.293*
When would the pandemic be over?			
In six months	*7.5%*	13.3%	**16.9%**
In a year	40.3%	*30.8%*	**46.5%**
In a year and half	**27.7%**	26.6%	*25.3%*
In two years or longer	24.5%	**29.3%**	*11.3%*
Inactive covariates			
Age group			
18-24	*9.4%*	13.0%	**14.5%**

Variable	*Tried a bit, but prefer going back.*	*Building new normalcy around WFH.*	*Planning on a short-term horizon.*
Share	**58.3%**	22.6%	*19.1%*
25-34	37.4%	*36.5%*	**38.2%**
35-44	**33.9%**	30.1%	*29.6%*
45-54	14.3%	**16.5%**	*13.8%*
55+	**5.1%**	3.9%	*3.8%*
Educational attainment			
Less than Bachelor's	28.0%	*27.3%*	**31.7%**
Bachelor's	48.5%	**49.3%**	*48.1%*
Postgraduate	**23.5%**	23.4%	*20.2%*
Work arrangement			
Work part time	*11.2%*	**14.7%**	13.8%
Work at multiple jobs	*4.0%*	5.0%	**5.3%**
Student status			
Study full time	*4.3%*	**6.7%**	6.0%
Study part time	**5.3%**	*4.6%*	5.4%
Primary commute mode			
Rail	50.6%	*44.8%*	**53.7%**
Bus	38.8%	**41.8%**	*36.2%*
Others	10.6%	**13.4%**	*10.1%*
Household characteristics			
N(household)	*3.398*	**3.442**	3.409
N(under 18)	0.304	**0.352**	*0.283*
N(18-64)	*2.575*	2.628	**2.642**
N(65 or older)	**0.472**	*0.409*	0.448
Presence of domestic helper(s)	*9.7%*	**13.2%**	10.3%
Monthly household income			
Under HK$20,000	*13.1%*	14.9%	**16.1%**
HK$20,000 to HK$39,999	32.7%	*31.7%*	**36.8%**
HK$40,000 to HK$59,999	*24.1%*	**24.8%**	24.6%
HK$60,000 or more	**30.1%**	28.7%	*22.5%*
Housing type			
Public housing	**28.6%**	*27.6%*	28.1%
Home ownership scheme flat	17.0%	*13.9%*	**18.5%**
Private housing estate	*38.7%*	**39.2%**	38.9%
Tenement house (with a lift)	*7.1%*	**8.3%**	7.4%
Tenement house (without a lift)	4.6%	**4.9%**	*4.4%*
Village house	4.0%	**6.1%**	*2.7%*
Housing tenure			
Rent	*37.8%*	38.2%	**42.3%**
Own	**47.1%**	45.9%	*42.8%*
Provided by someone else	15.1%	**16.0%**	*14.9%*
Current neighborhood (self-reported)			
Urban	*78.2%*	**79.2%**	78.8%
Suburban	**13.5%**	*11.0%*	12.3%
Rural	*8.3%*	**9.9%**	8.9%
Preferred neighborhood in the long run			
Urban	**73.1%**	*67.7%*	72.5%
Suburban	16.6%	19.4%	**21.3%**
Rural	10.3%	**13.0%**	*6.3%*
Attitudes on WFH			
Distracted while WFH	0.008	**0.016**	*-0.033*
Under control at home	0.016	**0.025**	*-0.023*
Online meeting is effective	*0.002*	0.023	**0.048**
Technology fails at home	*-0.027*	-0.020	**0.082**
General attitudes			
Pro-car	0.003	**0.031**	*-0.049*
Pro-transit-neighborhood	0.009	*-0.132*	**0.116**
Pro-waiting	*-0.001*	**0.063**	0.008
Pro-exercise	*-0.035*	**0.068**	0.045
Pro-technology	**0.013**	-0.015	*-0.051*
Life-satisfied	0.001	**0.088**	*-0.073*

Notes: Averages are computed for continuous variables, and shares are computed for discrete variables. The largest value in each row is **bolded**, and the smallest value in each row is ***<u>italicized and underlined</u>***. All covariates are inactive: i.e., they do not affect the probabilities of individuals belonging to certain latent classes, but help identify the individual, household, land-use, and attitudinal profiles of each class.

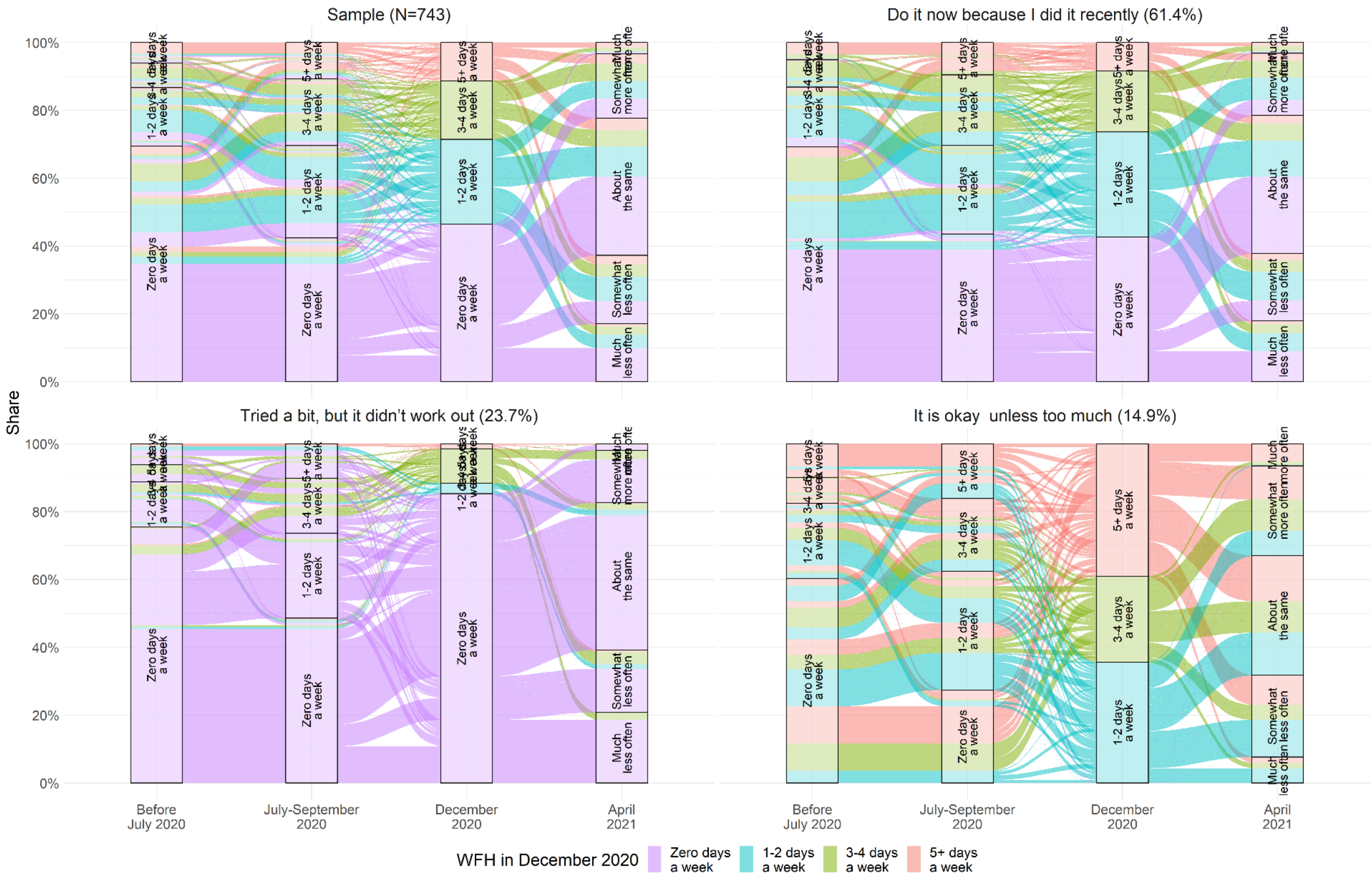

FIGURE A1 Alluvial Diagrams of WFH Frequencies at Four Timepoints from the Latent-Class Choice Model on the Present WFH Frequency

Notes: Out of 745 cases included in the LCCM, two cases were dropped because of missing values for the near-future expectation (this variable is not included as an active covariate).

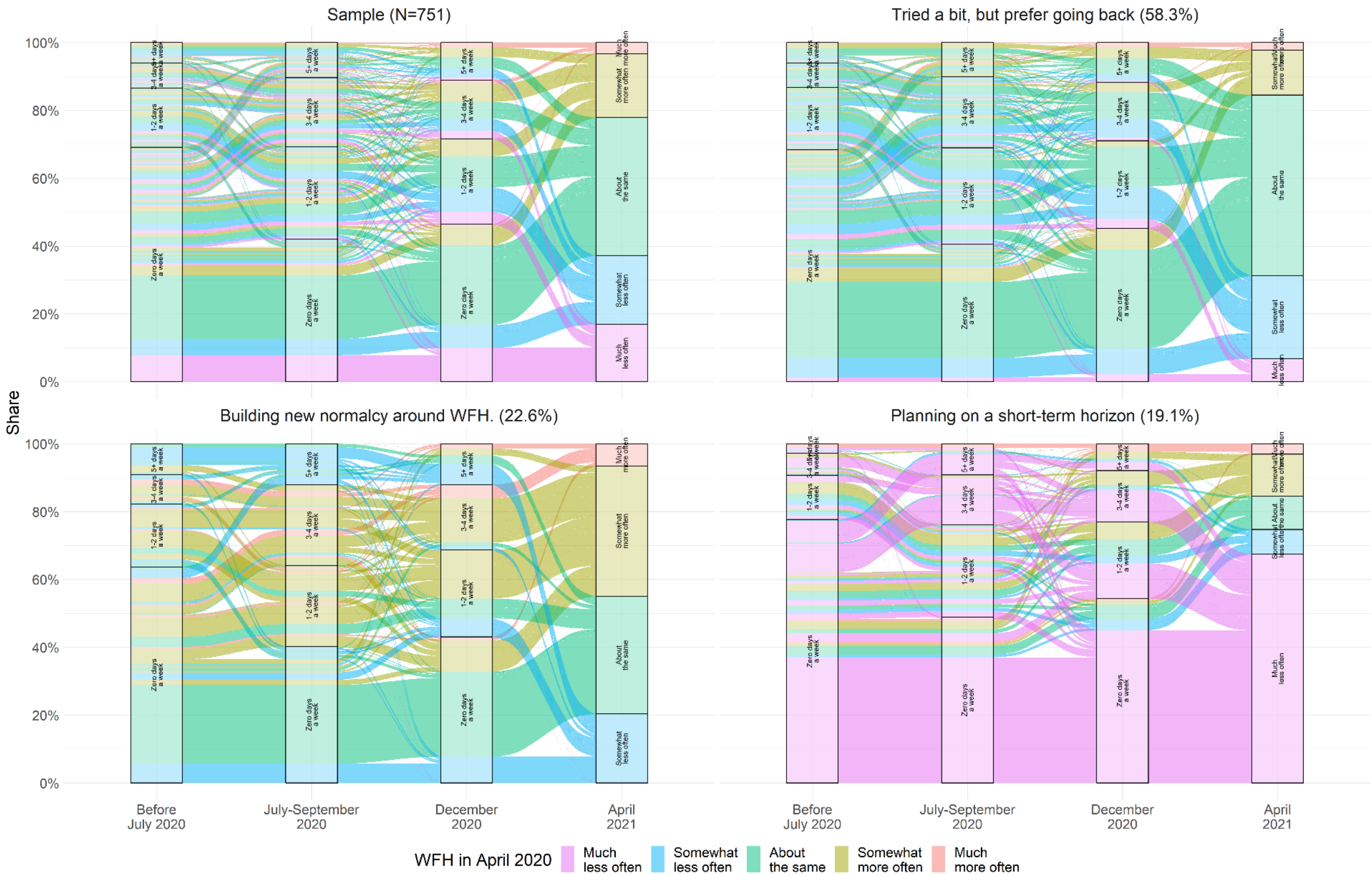

FIGURE A2 Alluvial Diagrams of WFH Frequencies at Four Timepoints from the Latent-Class Choice Model on the near-future WFH expectation

Notes: Out of 755 cases included in the LCCM, four cases were dropped because of missing values for the WFH frequency before July 2020 (this variable is not included as an active covariate).