Impacts of the walking environment on mode and departure time shifts in response to travel time change: Case study in the multi-layered Hong Kong metropolis

Abstract

Three-dimensional transportation space is one of the most important characteristics of multi-layered cities; however, fine-scale built environment factors about facilities that support the 3D walking environment were unavailable in understanding travelers' behaviors before heading to the Big Data era. Using both small (questionnaire survey) and big (large-scale geospatial) data, we conducted a case study in Hong Kong, a well-known vertical metropolis with a multi-modal transportation system. We analyzed mode and departure time shift behaviors in response to travel time change for 2,927 participants and examined the impacts of new variables derived from a 3D pedestrian network dataset and potential influencing factors identified in the literature. The results from the mode shift model indicated that having more efficient pedestrian networks, as measured by the total length of walkways and the provision of mobility aid facilities (e.g., travellators, escalators), is effective in promoting mode shift behaviors. Meanwhile, our departure time shift model revealed that having more comfortable walkways, as measured by travel attitude and the provision of mobility aid facilities, increases users' willingness to make departure time shifts from peak hours. These findings imply that a more efficient and comfortable walking environment facilitates mode and departure time shift behaviors in daily travel. Improving the building and management of walking environments would contribute to a more integrated multi-modal transport system.

Keywords: Mode shift; Departure time shift; Walkability; Transit access; Public transport; Hong Kong

1. Introduction

Transit-oriented development (TOD) is an efficient step toward achieving sustainable cities, especially in densely populated areas like Hong Kong (Tang and Lo, 2008, 2010). As travel demands are diverse, a multi-modal transport system, as the backbone of urban mobility, must integrate different modes to build an efficient transport system that supports different needs (Mees, 2014; Meng et al., 2020). To ease the pressure from land shortage and dense population, enabling multi-level city living in a vertical metropolis has been a fundamental consideration in urban planning and design practices for high-density cities (Shelton et al., 2013; Lau and Zhang, 2015; Al-Kodmany, 2018); however, it requires the recognition of diverse travel behaviors and their underlying factors, including the variety of transport modes and the walkability of different neighborhoods (Chan et al., 2021; Chan et al., 2022; Loo, 2021; Sun et al., 2017).

The three-dimensional transportation space is one of the most important characteristics of multi-layered cities. Urban transportation systems that perform smoothly include solutions dealing with topography such as exterior stairs, escalators, elevators, and bridges across man-made (e.g., traffic roads) and natural (rivers) obstacles that are typical for urban cities. People need to be able to move vertically in multi-layered cities, and this is also a crucial part of building connections between citizens and cities. González-González et al. (2021)'s study on Santander in Spain suggested that vertical walking facilities (e.g., escalators, moving sidewalks, lifts) are highly valued in mountainous cities, especially for those connecting to residential areas. A network of bridges with escalator pathways and moving walkways lined with shops, cafés, bars, and restaurants in Hong Kong's Central area has been shown as a successful case to provide both passage and entertainment (Zacharias, 2013), and later to a nearby hilly area (Nagamune and Kinoshita, 2016). On the other hand, some metro undergrounds are intended for the hilly environment, creating flat underground passageways, and some are for integration with more buildings and shopping malls (Shelton et al., 2013). Inhabitants in hilly neighborhoods, as recommended in ethnographic interviews in Lisbon, Portugal (Buhr, 2018) and Hong Kong, China (Sun and Lau, 2021), take advantage of metro stations' and malls' escalators to avoid walking up the steep slopes. Meanwhile, underground walking landscapes are also pipelines to transport pedestrians and certainly enlarge the metro station catchment (i.e., ease of station access by walking and other modes of transportation), as indicated qualitatively by walk-along interview (Sun and Lau, 2021) and quantitatively by stated preference survey (Cascetta and Cartenì, 2014) and pedestrian count observations (He et al., 2016; Zacharias and He, 2018).

Pedestrian facilities, as well as safe and pleasing environments, have long been identified as key factors to encourage walking (Cerin et al., 2014; Mateo-Babiano, 2016; Zegeer, 2002); nevertheless, such environment that facilitates circulation around transit stations are unevenly distributed (Barber, 2020). The same logic of efficiency and circulation guide planning and design in different kinds of urban spaces and cities continue to be built in transit-oriented cities like Hong Kong, particularly to integrate metro stations with other transportation modes and surrounding land uses. This article aims to answer a research question – *how do pedestrian facilities that support 3D pedestrian environment, affect travelers' mode and departure time shift behaviors, compared to other well-studied factors in the literature?* We adopted the latest regional travel survey to analyze mode and departure time shift behaviors and examined the influence of travel time increase for 2,927 participants in Hong Kong. By utilizing the newly released large-scale geospatial data of a three-dimensional (3D) pedestrian network, which provided more comprehensive data on walking environments, we derive variables of 3D pedestrian environment and meanwhile investigate potential influencing factors identified in the literature, including variables of sociodemographic and travel characteristics, transit accessibility, and the built environment obtained from multiple datasets.

2. Literature review

2.1 Influencers on mode and departure time shifts

Mode and departure time shifts as one of the changes in daily travel behaviors can be induced by short-term or longer-term disruptions/interventions, which could be in the form of travel time changes due to delays caused by traffic congestion and transit disruptions or improvement from the provision of new alternatives through new transport infrastructure and transit services. Travel time changes, in particular travel time increase as studied in this paper, is a major cause of mode and departure time shifts (Rahman and Baker, 2018).

2.1.1 Built environment

The impact of the built environment has been widely investigated (Li et al., 2021; Liu et al., 2021; Munshi, 2016; Schubert et al., 2020; L. Sun et al., 2021; Wang and Chen, 2012; Xiao et al., 2021), indicating the importance of the subject in explaining travel behaviors. The built environment has been largely quantified in terms of land use, population, and transport/walking infrastructure. The effects of the built environment might vary with context. For instance, by considering urban villages in Shenzhen, China as a case study, Yu et al. (2019) reported that transit availability is fundamental for promoting transit; however, the negative effect of density on transit mode choice and the non-effect of mixed land use contradict other studies. The built environment might only have indirect effects by influencing commuting characteristics; in contrast, attitudes (perception to a certain mode of travel) have both direct and indirect effects on commute satisfaction and commuting characteristics (Ye and Titheridge, 2017). Nevertheless, the built environment has been generally recognized as a significant variable in studies of travel characteristics.

2.1.2 Travel characteristics

Travel decisions are strongly correlated with trip characteristics and travel habits (Nguyen-Phuoc et al., 2018). Travel decisions vary according to trip purpose, journey time, mode choice, and first/last mile walking time. Travel distance plays an important role in the choice of transport mode (De Vos et al., 2022; Schwanen et al., 2004) as well as a mode switch from private transport to public transit (Yang et al., 2017). However, under a disruptive scenario (e.g., traffic congestion or a change of residential location), individuals prefer persisting with their habitual mode (Tsirimpa et al., 2007; Tang et al., 2015; Fatmi and Habib, 2017). The trip purpose also affects mode choice; for instance, rail commuters with bicycle theft experience are more likely to use public bicycles to access rail transit when making school- or work-related trips (Ji et al., 2017). Travel characteristics are typically included in models of travel decisions because of data availability, especially for studies based on national travel surveys as discussed in **Section 2.2**.

2.1.3 Socio-economic status

Sociodemographic is a fundamental variable in studies of travelers' behaviors (Carver et al., 2013; Prieto et al., 2017). The differences between, for instance, men and women, rich and poor, and younger and older, can directly or indirectly affect travel choices. Gender is a significant factor that influences travel behaviors. For instance, women are less likely to choose public transit than men (Patterson et al., 2005); in addition, male drivers are more willing to switch their travel mode to bus than female drivers (Rahman and Baker, 2018). Female workers are more likely to start their commutes earlier than males since they may be more likely to add secondary purposes on the way to work, such as escorting kids to school (Asgari and Jin, 2018). The difference in spatio-temporal travel characteristics of the elderly and young adults has been reported (e.g., Szeto et al., 2017; Shao et al., 2019). Apart from the individual perspective, households with more than one member have a lower propensity to switch toward car-sharing than people living alone or without relatives (Ceccato et al., 2021), whereas the presence of children and the addition of a car increase the propensity to transition from transit to car (Fatmi and Habib, 2016).

2.1.4 Attitude and lifestyle

Considering attitude and lifestyle could address the need to predict travel behaviors from a more humanized perspective (Wang and Chen, 2012; Fatmi and Habib, 2016; Lanzini and Khan, 2017). Differences in life cycle stages (e.g., studying, working, retired), socio-economic status, and living neighborhoods can influence how people value time, money, and comfort, which are the major factors in travel choices (de Donnea, 1972). Popuri et al. (2011) examined the effect of travelers' needs for reliable and stress-free commute, privacy and comfort, and tolerance of complexity (e.g., number of transfers) on transport mode choices. Abou-Zeid et al. (2012) investigated the effects of temporary disruptions in the mode of transportation to work on travel happiness and mode shift, claiming that disturbances in typical travel conditions cause people to reflect more deeply on their satisfaction with various forms of transportation. Sivasubramaniyam et al. (2020) found that social norms were a significant predictor of drivers' and car passengers' intentions to use the car.

Policymakers are keen to consider psychological factors when promoting various modes of transport, such as green and active transport. Hergesell and Dickinger (2013) suggested that encouraging general pro-environmental behaviors while improving citizens' environmental awareness can more efficiently promote green transport than traditional market-based interventions that considered various transport modes in terms of price, time, and convenience. Ingvardson et al. (2021) suggested that a traveler's self-concept/identity/esteem (a general term used to refer to how someone thinks about, evaluates, or perceives themselves) is highly related to daily travel mode choice. Aaditya and Rahul (2021) suggested that because of the Covid-19 pandemic, social distancing, masks, and personal sanitization have become the new lifestyle standards that significantly affect people's travel mode choices.

2.2 Data challenges and processes in travel behavioral studies

Urban designers have investigated how walking could be affected by the 3D pedestrian network comprised of extensive footbridges, metro undergrounds and paths inside malls (Karimi and Kasemsuppakorn, 2013; Zacharias, 2013). However, previous transport and health-related analyses mainly used road networks (Lu et al., 2016). In a 3D city like Hong Kong, it is an unreliable measure as the road network is strikingly different from the network that pedestrians navigate (Sun et al., 2021; Tang et al., 2020; Xu et al., 2022; Zhang and Chiaradia, 2022; J. Zhao et al., 2020). A call for the 3D realizations of pedestrian networks in a built environment so that the extent and fidelity can fulfill analytical methods for 3D problems has long been placed in the literature (Kwan and Lee, 2005; Lee, 2007; Thill et al., 2011; Sun et al., 2015). Previous studies have also identified issues in describing the built environment that people interact within high-density cities. A recent review on current practices of pedestrian accessibility assessment by Van Eggermond and Erath (2015) suggested that although data limitations are gradually overcome by using point-of-interest databases and online network data, network distances, however, are road centerline distances while some important pedestrian-related features such as crossings and building entrances are not included in the calculations. The extent and fidelity of 2D network data also affect the performance of sophisticated models. In the case of vertical cities, Guo and Loo (2013) found that the Hong Kong route choice model tends to perform less satisfactorily in terms of choice-set generation and final estimation. One explanation is that the pedestrian environment in Hong Kong, compared to New York, is more “complex, with hilly topography, many pedestrian bridges and underpasses, and the presence of public escalators and lifts” (p.135). This environment seems to affect the digitalization and utilization of the walking environment and perhaps travel behavioral assessment in general, especially in similar kinds of urban spaces like Hong Kong. A better measurement of (3D) complexity may help improve the modeling performance of travel behaviors.

Scholars have tried to combine multi-source (big) data to characterize fine-scale built environment factors in understanding traveler behaviors (Chen et al., 2016; Wang et al., 2018; Zannat and Choudhury, 2019). In this regard, regional/national travel surveys are commonly used to monitor long-term trends in personal travel and to inform policy development in cities, providing the basis for joining related spatial datasets. In Hong Kong, household surveys, specifically the Travel Characteristic Survey (TCS), are conducted every ten years. Over 35,000 households are interviewed to collect data on the travel characteristics of Hong Kong residents. TCS provides data on the travel patterns, transport mode preferences of residents, and residents’ use of private vehicles. Most studies integrate the TCS dataset with supplemental data according to their purposes. For example, local GIS datasets, including data on land use and transport/road network are common sources for data on the built environment, and past TCS datasets have been used in comparative studies. More recently, by integrating the web crawler technology on Google Street View with machine learning technique, some research groups have created a dataset of images to use in built environment evaluations (e.g., Yang et al., 2019, Tao and He, 2020). To supplement the low-dimensional network data and loss of three-dimensional (3D) details in the built environment evaluations, we examined various walking environments in Hong Kong using a 3D pedestrian network dataset. We investigated traveler’s mode and departure time shift behaviors that have not yet been studied in the existing TCS literature (see **Table 1** for a summary of studies using the recent TCS dataset).

Table 1 Studies using the most recent Travel Characteristic Survey (TCS)

Authors	Study focus					Target population		Factors			Supplementary dataset	
	Walking	Cycling	Transit	Accessibility	Mobility	All	Specific	Built environment	Travel characteristic	SES	General	Unique
Yao and Loo (2016)		✓				✓		✓	✓		Past TCS data, Land use GIS data	Traffic Road Accident Database
Xu et al. (2016)	✓					✓		✓			Local GIS data	Traffic Road Accident Database
Chow (2016)			✓			✓		✓			-	-
Guo et al. (2017)	✓					✓		✓			Transport network data	Territorial Population and Employment Data Matrix, Traffic Road Accident Database
Su et al. (2017)			✓			✓			✓			
Szeto et al. (2017)	✓		✓				Elderly		✓	✓	-	-
Lu et al. (2018)	✓					✓		✓		✓	Local GIS data	Google Street View
He et al. (2018)					✓		Elderly	✓	✓	✓	-	-
Tang et al. (2018)					✓	✓				✓	-	Air pollution data
Yang (2018)					✓		Elderly	✓	✓	✓	Local GIS data	-
Zhou and Wang (2019)					✓						Past TCS data	-
Lu et al. (2019)	✓						Youths	✓		✓	Population census	
Yang et al. (2019)	✓						Elderly	✓		✓	Land use GIS data, Population census	Google Street View
Zang et al. (2019)	✓				✓		Elderly	✓		✓		Google Street View
Lai et al. (2019)	✓		✓		✓	✓		✓		✓	-	-
Tao et al. (2020)					✓	✓				✓	Past TCS data	-
He et al. (2020)				✓	✓			✓		✓	-	-
Yang et al. (2020)					✓		Elderly	✓	✓	✓	-	Google Street View
Tao and He (2020)				✓			New town	✓		✓	Transport network data	-
This study			✓			✓		✓	✓	✓	Population census, Transport network, Land use data	3D pedestrian network data

3. Study area and data

3.1 Study area

Hong Kong is a high-density transit-oriented city and is well known for its high mode share in public transit accounting for over 90% of passenger trips. The transport policy in Hong Kong sets out a hierarchy of the roles and positions of the different public transport services, based on their efficiency and functions (Transport Department, 2017). At the top of this hierarchy is heavy rail, which operates on a dedicated rail corridor, providing high-capacity services. The next level consists of franchised buses and Light Rail, which serve as mass carriers and provide feeder services to heavy rail. Other public transport services play a supplementary role. For instance, public light buses are used for routes with relatively lower patronage, taxis offer personalized and point-to-point services for commuters who are willing to pay a higher fare, and ferries provide outlying island passengers with essential transport services and cross harbor passengers with another mode choice through inner harbor routes. Nevertheless, such high mode shares and good service levels still require extra soft and hard efforts from policy measures and infrastructure to integrate the services across all travel modes (Wang and Po, 2001; Luk and Olszewski, 2002; Zhe, 2017). Examples could be the off-peak travel discount, a transit demand management policy that targets trip scheduling by regular commuters, which aims at spreading peak loading (i.e., departure time shift) and achieving uniform diurnal ridership (Halvorsen et al., 2016, 2020; Anupriya et al., 2020), and mode shift to rail policy such as the continuous expansion of the metro network with bus route rationalization (Tang and Lo, 2008, 2010; Chan et al., 2021a). This study investigates the impact of walking environment on promoting mode and departure time shift intentions.

3.2 Data

3.2.1 Questionnaire survey data

The choice behavior data were obtained from the TCS of 2011, which was conducted by the Transport Department to study travel patterns among Hong Kong residents. The 2011 TCS consists of one main survey and five linked supplemental surveys, one of which focuses on travel propensity.

The sample for the main travel survey included 101,385 residents of 35,401 households who were spatially distributed throughout the territory of Hong Kong. Interviews were conducted by trained interviewers who collected data about participants' demographic and household information, as well as travel behaviors. In the main travel survey, respondents reported detailed information about any trips, including walking trips, made during the reference 24-hour period. When respondents reported a first trip made during peak hours (i.e., 7 a.m. to 10 a.m. and 5 p.m. to 8 p.m.) in which mechanized[1] transport was used, they were asked to do a supplementary survey on mode and time shift behavior related to that trip in response to the

[1] In travel demand forecasting, the term "*mechanized trips*" is used in the UK, which is the same as "*motorized trips*" used in the USA (see Boyce and Williams, 2015). In Hong Kong, "*mechanized transport*" includes 9 major transport modes, including mass transit railway (MTR), light rail transit (LRT), tram, ferry, public light bus (PLB), franchised bus, private vehicle, taxi and special purpose bus (SPB).

travel time change. For this study, we identified the participants who had completed the supplementary survey; this provided an analytic sample of 2,927 participants.

3.2.2 Three-dimensional pedestrian network dataset

This study used the three-dimensional (3D) models of pedestrian networks made available by the Hong Kong Government (2020) under the Open and Big Data Plans (**Figure 1**). The new dataset provided images with a high spatial resolution and rich information (readers are referred to a comparative study between old road networks and newly built networks (Sun et al., 2021).

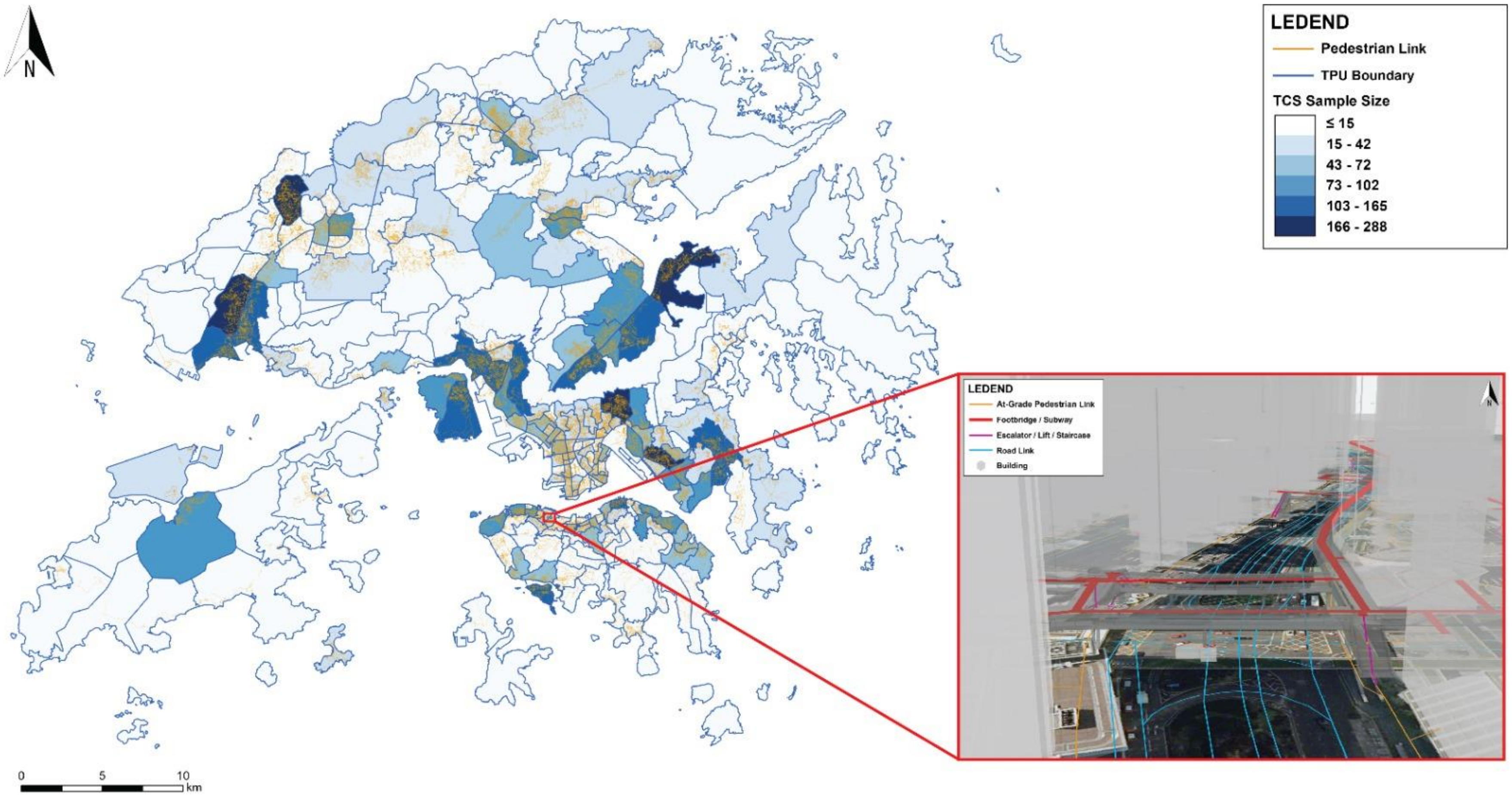

Figure 1 2D and 3D view of the pedestrian network. *Note*: For town planning purpose, the whole territory of Hong Kong is divided into 291 Tertiary Planning Units (TPUs) by the Planning Department. Over 70% of Hong Kong is comprised of open spaces, including country parks, reservoirs and other non-urban areas and digitized pedestrian networks are located mainly in the remaining 30%. Areas that contain very few or no pedestrian links were removed from our analysis.

4. Methodology

4.1 Mode and departure time shift models

Our mode and departure time shift models are developed using the binary logistic regression (BLR) method because it is the most practical and easily applicable method when considering stated preference (SP) data (Dissanayake and Morikawa, 2010; Zhao et al., 2020; Vasudevan et al., 2021). Details about BLR are not described here because adequate studies have done this (e.g., see Vasudevan et al., 2021).

We adopted the data collected from a regional travel survey (i.e., TCS Attachment Survey 2). Respondents who had made mechanized[2] trips during peak hours on the reference weekday (the day which the respondent's trip log data was recorded in TCS Main Survey) were asked whether they would change their travel pattern (i.e., mode/time shift) if the travel time of their trips were increased by 25%, 50%, and 100% respectively, on the reference trip during peak hours. Since we have no information about which mode and what time they would shift to, the responses are coded as dichotomous values in the binary logit mode shift model. **Figure 2** shows sample questions in the supplementary survey on mode shift and departure time shift with different increments in traveling time. For the statements of whether they would (i) "switch to another mode of transport" and (ii) "avoid starting the trip from 7 a.m. to 10 a.m. / 5 p.m. to 8 p.m.," we set 1 for "Yes" and 0 for "No" and "Don't know/ unsure."

ASII.7 If future travel conditions changed, and this trip would have to take (read out items a to c regarding the percentage of increase in travelling time) more than it did yesterday, would you (read out the action item)?

If "Yes", ask next action item; otherwise, ask next item regarding the percentage of increase in travelling time.

(Read out items i – ii in rotation)	(a)25%	(b)50%	(c)100%
(i) Switch to another mode of transport			
Yes	1- Skip to next item (iia)	1- Skip to next item (iia)	1
No..	2 Continue (ib)	2 Continue (ic)	2 Continue (iia)
Don't know/ unsure........................	9	9	9
(ii) Avoid starting the trip during 7 a.m. to 10 a.m. / 5 p.m. to 8 p.m.			
Yes	1-Skip to ASII.8	1- Skip to ASII.8	1
No..	2 Continue (iib)	2 Continue (iic)	2
Don't know/ unsure........................	9	9	9

Figure 2 Part of the questionnaire regarding preferences in mode shift and departure time shift (adopted from Transport Department, 2014)

We assess the main determinants of the mode shift, defined as a change in the current choice driven by the introduction of the new travel conditions. The predictor variables considered are categorized into personal socio-demographic characteristics, travel characteristics, and neighborhood-built environment characteristics, including land use characteristics and walking environment. Here, dummy variables for each scenario (i.e., a 25%, 50%, and 100% increase in travel time) are developed to analyze the effect of travel time increase on mode shift behavior. Final models are developed based on variables with $p < 0.1$ in trial models.

[2] While Hong Kong is a high-density transit-oriented city and is well known for its high mode share in public transit accounting for about 90% of daily mechanized trips. In this study, we focus on public transport users, who used public transport modes for their first trip reported in the survey.

4.2 Independent variables from multiple data sources

Inspired by many aforementioned studies, we decided to conduct an empirical study in Hong Kong of the mode and departure time shifts in response to travel time changes and their influencers, primarily based on the national travel survey and open spatial data.

Building on the TCS data, we collected data on independent variables from multiple sources: a) a large-scale 3D pedestrian network from the HKSARG Lands Department (2020) for walking environment data; b) the population census of 2011 from the HKSARG Census and Statistics Department (2013) for neighborhood characteristics data; c) Outline Zoning Plans (OZPs) from the HKSARG Planning Department (2019) for land use data; and d) General Transit Feed Specification (GTFS) for public transit data. Area-based variables were derived at the level of Tertiary Planning Units (TPUs), which divide the entire territory of Hong Kong into 291 units, which form the basis for land use and transport planning in Hong Kong. We used ArcGIS Pro 2.8 to derive the attributes of Hong Kong's pedestrian network from the 3D dataset (links = 436,426, nodes = 371,971). We established dummy variables for representing different groups of travelers regarding their departure time by hours (i.e., first, middle, last hour of morning and evening peak). The classification is justified by the Early Bird Discount pricing intervention in Hong Kong that fare discount is offered to travelers who conduct their trips during the 'first' hour of peak (Anupriya et al., 2020) and patronage loads peak in the middle hour (i.e., Halvorsen et al., 2020).

Adopting multiple data sources allowed us to test our model with independent variables from the following categories: walking environment, travel characteristics, attitude, socio-demographic characteristics, transit availability, and neighborhood characteristics. **Table 2** summarizes the independent variables, corresponding categories, and data sources.

Table 2 Descriptive statistics of dependent and independent variables

Attribute	Acronyms	Data source	Statement/questions	Code	Mean (S.D)
Travel characteristic					
Trip purpose: commuting (work/school)	PUR	TCS	Trip purpose	1: commuting trip (work/school); 0: non-commuting trip	0.76 (0.426)
Journey duration	DUR	TCS	Journal time (mins)		43.95 (21.045)
Walk >10 min	WALK	TCS	Walking time	1: ≥10 mins; 0: <10 mins	0.06 (0.232)
Driving habit (at least once per week)	DRIVE	TCS	Over the past 12 months, how often did you drive in Hong Kong?	1: at least once per week; 0: less than once per week	0.14 (0.348)
Departure time			Departure time of reference trip		
Early Bird (AM)	EB_AM	TCS	First hour of morning peak (7 – 8 am)	1: Yes; 0: No.	0.29 (0.453)
Early Bird (PM)	EB_PM	TCS	First hour of evening peak (5 – 6 pm)	1: Yes; 0: No.	0.07 (0.258)
Late Bird (AM)	LB_AM	TCS	Last hour of morning peak (9 – 10 am)	1: Yes; 0: No.	0.19 (0.396)
Late Bird (PM)	LB_PM	TCS	Last hour of evening peak (7 – 8 pm)	1: Yes; 0: No.	0.05 (0.214)
Load Peak	LP	TCS	Load peak (8 – 9 am & 6 – 7 pm)	1: Yes; 0: No.	0.40 (0.489)
Transport mode taken			Hierarchy of transport modes of sample of daily trips	MTR/ Bus/ PLB/ PV/ Taxi/ Others	
PLB	PLB	TCS	PLB	1: Yes; 0: No.	0.11 (0.309)
Bus	BUS	TCS	Bus	1: Yes; 0: No.	0.29 (0.454)
Metro	METRO	TCS	MTR	1: Yes; 0: No.	0.45 (0.497)
Private vehicle	PV	TCS	PV	1: Yes; 0: No.	0.08 (0.271)
Taxi	TAXI	TCS	Taxi	1: Yes; 0: No.	0.02 (0.137)
Other	OTHER	TCS	Other	1: Yes; 0: No.	0.36 (0.481)
Attitude			What is the main factor affecting your choice of taking public transport when going out?	Travel time/ Costs/ Comfort	
Pro-time	ATT_Tim	TCS	Travel time	1: Yes; 0: No.	0.46 (0.499)
Pro-cost	ATT_Cos	TCS	Costs	1: Yes; 0: No.	0.12 (0.321)
Pro-comfort	ATT_Com	TCS	Comfort	1: Yes; 0: No.	0.58 (0.494)
Socio-economic					
Household size	HOUSE	TCS	Household size	Discrete variable	3.01 (1.357)
Vehicle ownership	VEH	TCS	Household vehicle ownership	1: Yes; 0: No	1.82 (0.400)
Home location: urban	URBAN	TCS	Address TPU&SB code	1: Hong Kong Island/Kowloon; 0: Others	0.56 (0.497)
Income	INC	TCS	Household income	Discrete variable	10.76 (9.331)
Male	MALE	TCS	Sex	1: Male; 0: Female	0.51 (0.500)
Age	AGE	TCS	Age	Discrete variable	42.37 (15.069)
Full-time employee	FT	TCS	Employment condition	1: Yes; 0: No	0.75 (0.433)

Walking environment				
Total pedestrian length	PedLen	3DPN	Total length (m) walkway in the origin TPU of trip	65188.19 (44540.969)
Indoor (%)	INDOOR	3DPN	Percentage of indoor walkway in the origin TPU of trip	0.057 (0.045)
Cover (%)	COVER	3DPN	Percentage of covered walkway in the origin TPU of trip	0.150 (0.079)
Aid (%)	AID	3DPN	Percentage of mobility aided walkway in the origin TPU of trip	0.004 (0.005)
Transit availability				
No. of bus stops	BUSst	GTFS	Number of bus stops in the origin TPU of trip	669.53 (983.544)
Distance to nearest metro station	METROst	GTFS & TCS	Distance to the nearest metro station from the centroid of origin TPU of trip	0.03 (0.053)
Neighborhood				
Population	POP	Census	Population of the origin TPU of trip	81709.82 (63839.345)
Land use (%)			Percentage of different types of land use in the origin TPU of trip	
Commercial	LAND_C	OZP	Percentage of commercial land use	0.03 (0.053)
Industrial	LAND_IND	OZP	Percentage of industrial land use	0.02 (0.052)
Institutional	LAND_INS	OZP	Percentage of institutional land use	0.11 (0.071)
Open Space	LAND_O	OZP	Percentage of open space land use	0.12 (0.109)
Residential	LAND_R	OZP	Percentage of residential land use	0.26 (0.138)
Transport	LAND_T	OZP	Percentage of transport land use	0.18 (0.116)
Dependent variable				
Mode Shift @25%	MS.25	TCS	Decision on mode shift when travel time increased by 25%. 1: Yes; 0: No.	0.52 (0.5)
Mode Shift @50%	MS.50	TCS	Decision on mode shift when travel time increased by 50%. 1: Yes; 0: No.	0.57 (0.496)
Mode Shift @100%	MS.100	TCS	Decision on mode shift when travel time increased by 100%. 1: Yes; 0: No.	0.65 (0.477)
Time Shift @25%	TS.25	TCS	Decision on time shift when travel time increased by 25%. 1: Yes; 0: No.	0.23 (0.42)
Time Shift @50%	TS.50	TCS	Decision on time shift when travel time increased by 50%. 1: Yes; 0: No.	0.34 (0.473)
Time Shift @100%	TS.100	TCS	Decision on time shift when travel time increased by 100%. 1: Yes; 0: No.	0.39 (0.488)

Notes: TCS: Travel Characteristic Survey 2011; 3DPN: 3D-pedestrian network; GTFS: General Transit Feed Specification; Census: Population Census 2011; OZP: Outline Zoning Plans

5. Results and discussions

Table 3 and **Table 4** summarize the estimation results of the mode and departure time shift models, respectively. The overall model prediction accuracy was satisfactory (i.e., predictivity > 60%) and the final models are with all variables with $p < 0.10$ and shows an improvement in predictivity. The estimated effects indicate that the greatest impact (i.e., highest coefficient) on mode and departure time shifting intentions is from one (or more) measures of the 3D walking environment. Other factors, including travel characteristics, attitude, and neighborhood characteristics, have varying effects on mode and departure time shift intentions. The remainder of this section discusses the results in more detail.

5.1 Influence of walking environment

Mode shift. The coefficients of walking environment attributes were generally high. Among all the variables, *covered and moving walkways* played a major role in facilitating mode shift behavior. This could imply that higher convenience and comfort promote shifting to other alternative modes. In contrast, a higher percentage of *indoor walkways* promoted loyalty to the current modes of transport. This observation might be because indoor walkways are typically located in shopping malls, which have lower connectivity to outdoor walkways that connect to the road transport system.

Departure time shift. Although the walking environment had a weaker effect on the choice of departure time shift than on mode shift, people's willingness to shift was positively associated with the *availability of mobility aid facilities* and negatively associated with the *proportion of indoor walkways* where they live. It can be argued that mobility aid facilities provide a faster means of travel whereas indoor routes do not necessarily mean a more comfortable walking environment. This is coherent with the results of travelers' attitudes that individuals who valued comfort more highly were more willing to switch to non-peak hours to avoid crowds.

5.2 Influence of neighborhood characteristics

Mode shift. *Land use* variables, together with *population*, generally had low significance or a low coefficient, indicating that these neighborhood characteristics have a low impact on shifting behaviors. *Transit availability*, which is evaluated by the distance between the residence and the nearest metro station, and the number of bus stops in the residence area, is not directly associated with the intention to shift to other modes. It is because an aggregate availability index might not reflect the disaggregate route level service availability. Finally, it can be observed that socio-demographics generally affected mode shift behaviors. Females with a full-time job, of lower age, earning a high income, and living in urban areas were more likely to switch from their current modes when expected travel time increases considerably.

Departure time shift. People living in more *commercialized neighborhoods* and/or with more *transport infrastructure* were less likely to shift their departure times. This observation could be due to the higher supply and low demand for transit services that make traveling more comfortable in less crowded conditions.

5.3 Influence of travel characteristics

Mode shift. *Walking and driving behaviors* had opposite effects on mode shift: the intention of shifting to other modes increased with the travelers' driving behavior and decreased with their walking behavior. In contrast, *trip purpose* and *journey time* did not affect mode shift behavior. Considering the *departure time* of reference trip, 'early bird' travelers were less likely to shift to other modes of transport, in contrast to 'late bird' travelers, indicating varying flexibility to shift their modes in different time periods, such as special-purpose bus (SPB) services in earlier peak hours. Regarding the *transport mode* taken, users of private vehicles and supplementary public transit were more loyal to their current transport modes, whereas bus and taxi riders were sensitive to travel time change and were more likely to switch to alternative modes. The distinct qualities of the private vehicle mode, such as direct door-to-door service, comfort and privacy (Urbanek, 2021), while the SPB's non-substitutable routing for specific purposes (Rusco and Walls, 2001), tram's extremely low fare (Yang and Zacharias, 2017), and ferry as sea transport for specific geographical contexts (Tsoi and Loo, 2021), may not be easily offered by public transport modes.

Departure time shift. *Longer-distance* travelers were more willing to shift their time of departure in non-peak hours. It may be due to the increasing uncertainty regarding travel time increase for longer-distance trips. Considering the *departure time* of reference trips, 'late bird' travelers, were less likely to shift to non-peak departure time, recognizing there may be little flexibility to adjust the time in making 'late' trips. Looking at the *transport mode* taken, the shift intention of bus and private vehicle riders/drivers is lower compared to riders of other modes. The unique properties offered by these modes might be temporally bounded, for instance, special bus services during specific time periods and time-related car parking rules and restrictions.

5.4 Influence of Socio-demographic status

Mode shift. *Home location* is of the largest impact on mode shift behavior among other socio-demographic variables. Those living in the urban area would change their travel modes, possibly due to more choices as compared to the rural area. Individuals with higher *income* were more willing to shift to other modes, recognizing the cost/fare flexibility offered by their financial status. This can be seen together with *travel attitude*, people who considered time as being more valuable were more likely to shift modes to save time. Meanwhile, the intention to shift to other modes decreased with their *age*, considering those younger might be more knowledgeable and more receptive to changes across modes than those older. *Full-time employees* were more willing to shift to other modes, recognizing the time constraints from their employment status that lower the tolerance to travel time increase and necessitate the mode shift. In contrast, household size, vehicle ownership and sex did not significantly affect mode shift behavior.

Departure time shift. Compared to the mode shift behaviors, socio-demographic status did fewer effects on the departure time shift behavior: household size, vehicle ownership, sex, age, and employment status did not significantly affect departure time shift behavior. *Home location* and *income*, again, had a considerable effect on departure time shift behavior: an urban environment potentially offers more amenities while higher income enables elasticities for departure time shift behavior.

Table 3 Estimation results of mode shift decision model

	Trial model			Final model		
Dep Var: Mode shift decision	Std. Coef.	Std. Error	Sig.	Std. Coef.	Std. Error	Sig.
Travel condition: Travel time increase						
50% increase	0.86***	0.055	0.000	0.86***	0.055	0.000
100% increase	1.21***	0.056	0.000	1.21***	0.056	0.000
Ref: 25% increase						
Travel characteristic						
Trip purpose: commuting (work/school)	0.03	0.080	0.704			
Journey duration	0.00	0.001	0.968			
Walk >10 min	0.16***	0.102	0.001	0.16***	0.101	0.001
Driving habit (at least 1 time per week)	-0.14**	0.085	0.022	-0.16***	0.080	0.005
Departure time						
Early Bird AM	0.03	0.057	0.518	0.03	0.056	0.554
Early Bird PM	-0.17***	0.096	0.001	-0.17***	0.095	0.001
Late Bird AM	0.10*	0.064	0.058	0.10*	0.064	0.057
Late Bird PM	0.01	0.111	0.790	0.02	0.110	0.694
Ref: Load Peak						
Transport mode taken						
PLB	0.04	0.079	0.451	0.04	0.078	0.471
Bus	0.37***	0.110	0.000	0.37***	0.109	0.000
Private vehicle	-0.27***	0.113	0.000	-0.30***	0.105	0.000
Taxi	0.10*	0.193	0.051	0.10*	0.192	0.051
Other: Ferry/ Tram/ SPB	-0.35***	0.107	0.001	-0.35***	0.106	0.001
Ref: Metro/Light rail						
Attitude						
Time	0.49***	0.076	0.000	0.50***	0.075	0.000
Comfort	-0.13*	0.076	0.072	-0.15**	0.075	0.048
Ref: Cost						
Socio-demographic						
Household size	-0.08*	0.018	0.088	-0.09*	0.017	0.058
Vehicle ownership	0.07	0.072	0.224			
Home location: urban	0.28***	0.065	0.000	0.26***	0.058	0.000
Income	0.15***	0.003	0.001	0.15***	0.003	0.001
Male	-0.10**	0.048	0.043	-0.09*	0.047	0.062
Age	-0.15***	0.002	0.006	-0.15***	0.002	0.002
Full-time employee	0.18***	0.072	0.005	0.19***	0.055	0.000
Walking environment						
Total pedestrian length	0.00***	0.000	0.005	0.00***	0.000	0.002
Indoor (%)	-0.65***	0.945	0.000	-0.65***	0.910	0.000
Cover (%)	0.36***	0.541	0.000	0.33***	0.511	0.000
Mobility aid facilities (%)	0.31***	7.182	0.000	0.32***	6.987	0.000
Transit availability						
Number of bus stops	-0.09	0.002	0.163			
Distance to nearest metro station	0.00	0.000	0.399			
Neighborhood						
Population	0.00	0.000	0.167			
Commercial (%)	-0.12**	0.562	0.048	-0.11*	0.519	0.050
Industrial (%)	0.00	0.505	0.999			
Institutional (%)	0.05	0.338	0.328			
Open space (%)	0.06	0.228	0.225			
Residential (%)	0.17***	0.210	0.004	0.17***	0.187	0.001
Transport (%)	0.05	0.245	0.367			
Constant	-1.36***	0.226	0.000	-1.07***	0.155	0.000
-2 Log likelihood	11147.028			11156.691		
Cox & Snell R square	0.108			0.107		
Negaelkerke R Square	0.145			0.143		
Overall prediction (%)	64.5%			64.7%		

Note: *p < 0.10, **p < 0.05, ***p < 0.010. SPB: special-purpose bus, including school bus and residential service.

Table 4 Estimation results of departure time shift decision model

	Trial model			Final model		
Dep Var: Departure time shift decision	Std. Coef.	Std. Error	Sig.	Std. Coef.	Std. Error	Sig.
Travel condition: Travel time increase						
50% increase	0.55***	0.060	0.000	0.55***	0.060	0.000
100% increase	0.79***	0.059	0.000	0.79***	0.059	0.000
Ref: 25% increase						
Travel characteristic						
Trip purpose: commuting (work/school)	-0.02	0.083	0.772			
Journey duration	0.18***	0.001	0.002	0.18***	0.001	0.003
Walk >10 min	0.03	0.101	0.616			
Driving habit (at least 1 time per week)	0.01	0.089	0.847			
Departure time						
Early Bird AM	0.08	0.058	0.170	0.07	0.057	0.226
Early Bird PM	0.00	0.098	0.963	0.02	0.094	0.734
Late Bird AM	-0.28***	0.068	0.000	-0.26***	0.067	0.000
Late Bird PM	-0.27***	0.125	0.000	-0.25***	0.124	0.000
Ref: Load Peak						
Transport mode taken						
PLB	0.02	0.082	0.680	0.01	0.081	0.851
Bus	-0.19*	0.111	0.083	-0.19*	0.110	0.080
Private vehicle	-0.20***	0.121	0.004	-0.22***	0.101	0.000
Taxi	0.01	0.196	0.927	0.01	0.195	0.922
Other: Ferry/ Tram/ SPB	0.10	0.108	0.350	0.11	0.107	0.311
Ref: Metro/Light rail						
Attitude						
Time	0.02	0.078	0.779	0.00	0.077	0.999
Comfort	0.18*	0.078	0.033	0.19*	0.077	0.023
Ref: Cost						
Socio-demographic						
Household size	-0.08	0.018	0.122			
Vehicle ownership	0.01	0.075	0.828			
Home location: urban	0.20***	0.068	0.008	0.19***	0.053	0.001
Income	0.10**	0.002	0.047	0.08*	0.002	0.070
Male	-0.01	0.049	0.897			
Age	0.03	0.002	0.460			
Full-time employee	-0.04	0.074	0.586			
Walking environment						
Total pedestrian length	0.00	0.000	0.769			
Indoor (%)	-0.46***	0.982	0.000	-0.47***	0.706	0.000
Cover (%)	-0.10	0.547	0.279			
Mobility aid facilities (%)	0.39***	7.314	0.000	0.37***	7.173	0.000
Transit availability						
Number of bus stops	-0.05	0.002	0.520			
Distance to nearest metro station	0.00**	0.000	0.016	0.00**	0.000	0.034
Neighborhood						
Population	0.00	0.000	0.135			
Commercial (%)	-0.19***	0.601	0.005	-0.22***	0.548	0.000
Industrial (%)	0.11*	0.522	0.059			
Institutional (%)	0.20***	0.345	0.000	0.19***	0.334	0.000
Open space (%)	0.07	0.235	0.237			
Residential (%)	0.06	0.217	0.363			
Transport (%)	0.19***	0.251	0.002	0.19***	0.235	0.002
Constant	-1.76	0.236	0.000	-1.69	0.121	0.000
-2 Log likelihood	10585.881			10600.652		
Cox & Snell R square	0.045			0.043		
Negaelkerke R Square	0.063			0.061		
Overall prediction (%)	68.5%			68.5%		

Note: *p < 0.10, **p < 0.05, ***p < 0.010. SPB: special-purpose bus, including school bus and residential service.

6. Planning implications

The 3D pedestrian dataset, comprised of extensive footbridges, metro undergrounds and indoor and outdoor pedestrian facilities, supports the evaluation of complex walking environments; meanwhile, household travel surveys provide an opportunity to link mode and departure time shift behaviors with the spatial datasets, and demographics, socio-economic characteristics, and trip purposes of individual passengers from a large representative sample. Several key implications regarding mode and departure time shift behaviors across individuals living in different built environments and with different socio-demographic backgrounds emerge from the current analysis. This section presents the implications of these issues on transit operations and transportation policy.

Having more efficient pedestrian networks with more mobility aid facilities (e.g., travellators, escalators) promotes mode shift behaviors. Mode shift behaviors are receiving attention from policymakers seeking to reduce car use/reliance and from transit operators developing strategic interactions to reduce inter-modal competition. Common tools for promoting efficiency include economic (subsidy, reward system, penalty), communicative (written materials, behavioral elements), and physical (providing bicycles and better bicycle facilities at work to adjust the environment) strategies (Scheepers et al., 2014). Our results demonstrate that private vehicle riders/drivers are stickier than public transit riders. However, providing better walking environments for the first/last mile might facilitate public transit ridership. This provision is likely to be more effective in urban areas where traffic congestion is common. Although it involves the investment of money and time, it generally yields more benefits by leveraging a better living environment.

More comfortable walkways, as suggested by travel attitude to comfort and availability of mobility aid facilities, increase the willingness of travelers to shift departure times. Promoting departure time shifting from peak hours is a common strategy in transportation demand management. The strategy is used to reduce congestion in crowded public transportation systems (Anupriya et al., 2020; Halvorsen et al., 2020; Yang et al., 2022). A common practice is to provide incentives (e.g., fare reduction) to encourage traveling at non-peak hours. Our results provide an alternative strategy for promoting such behaviors: improving the comfort of pedestrian networks around the transit stations. This alternative is expected to be more effective in residential areas where people commute longer distances. It is preferable to build these types of walking amenities along pedestrian routes in locations with a considerable population to justify their investment and maintenance expenses, rather than focusing only on well-equipped central districts.

The study of impact of socio-demographic and travel attitudes on travel behaviors is relevant because it reveals potentially disadvantaged subgroups. For example, older adults in our study preferred to stick to the original travel plan even if travel time was significantly increased, and a potential reason could be due to the ability to access travel information (Chorus et al., 2006; Grotenhuis et al., 2007). Despite the fact that shifting demands related to their attitudes towards trade-off between time, cost, comfort (Aschauer et al., 2019), and resulting information demands may vary from person to person (Shrestha et al., 2017): some older persons can access information using modern technology (e.g., smartphones) whereas others rely only on printed materials; some passengers may be willing to spend more time on the pre-determined mode rather than embarking on a route that necessitates a change of mode, promoting information exposure among older people might make them may feel more comfortable with their possible options and, as a result, more satisfied with their overall transportation mobility if they have greater information about different modes of transportation (Ravulaparthy et al., 2013).

7. Conclusions

This paper adopted a new 3D pedestrian network dataset and used Hong Kong's household travel survey to investigate the mode and departure time shift of peak hour trips recorded on the surveyed travel days. It also examined the associations between shift behaviors and a series of travel characteristics, attitude, socio-demographic, transit availability and neighborhood characteristic factors. Both models of mode and departure time shift reveal the importance of addressing 3D walking environments, especially for pedestrian facilities. This finding suggests that improving the walking environment might help transport policymakers and transit operators to promote such shift behaviors toward an integrated multi-modal transport system.

We acknowledge both strengths and limitations of our study. The strengths of this study include its large representative sample from a regional travel survey and measures of the 3D walking environment. Secondary data analyses are associated with some limitations. The results are based on Tertiary Planning Unit (TPU), which is the smallest unit for planning purposes in Hong Kong and a common analytic unit among literature using the same dataset (e.g., Chow, 2016; Yao and Loo, 2016; Tao et al., 2020), and thus are of potential for comparative purpose and planning implications. A finer analytic unit for evaluating the walking environment, for instance, looking at the exact route respondents used to access transit services would be promising in future research. While quantitative methods might be insufficient for understanding how pedestrian environments influence the intention of shifting behaviors of public transport users, qualitative research is becoming increasingly relevant in high-density cities like Hong Kong to understand and address diverse local factors. Moreover, the exploratory analysis relies on a relatively old survey dataset. The survey did not ask questions that allowed us to identify the exact transport mode and departure time respondents shifted to. The scenario might also not be applicable in new travel and social environments, especially for post COVID-19 conditions (Chan et al., 2021b).

Future research based on a more updated and detailed travel survey will yield more accurate user responses and better control of other factors, such as lifestyle characteristics. The next regional travel survey in Hong Kong is currently being conducted in 2021-22, and data collected will be potentially integrated with local smart cards and in-mobile application data (Ng, 2019). As we are entering the era of big data, travel survey researchers will need to use passive big data to complement traditional survey data, such as smartphones (Hong et al., 2021; Wong et al., 2021), smart cards (Zhou et al., 2020), Wi-Fi (Kouřil and Šimeček, 2020) dataset. An updated sample with big data could facilitate the development of a more comprehensive model for testing hidden variables and associations between them. A panel analysis in conjunction with a survey will aid in predicting switch behaviors in the constantly changing urban environment.

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