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Effects of proactive and reactive health control measures on public transport preferences of passengers – A stated preference study during the COVID-19 pandemic

Tiantian Chen[a], Xiaowen Fu[b,*], David A. Hensher[c], Zhi-Chun Li[d], N.N. Sze[e]

[a] *Cho Chun Shik Graduate School of Mobility, Korea Advanced Institute of Science and Technology, South Korea*
[b] *Behavior and Knowledge Engineering Research Centre, Department of Industrial and Systems Engineering, Hong Kong Polytechnic University, Hung Hom, Kowloon, Hong Kong*
[c] *Institute of Transport and Logistics Studies, The University of Sydney Business School, The University of Sydney, Australia*
[d] *School of Management, Huazhong University of Science and Technology, Wuhan, China*
[e] *Department of Civil and Environmental Engineering, The Hong Kong Polytechnic University, Hung Hom, Kowloon, Hong Kong*

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ABSTRACT

The outbreak of COVID-19 has caused unprecedented disruptions to public transportation services, passengers' mode choice preferences, and their behavioral pattern. Recent studies have updated the systemic shift from shared travel to private mode due to the perceived higher health risk of shared mobility. However, findings from these studies may not be applicable to public transport-oriented cities with very low rate of private car ownership. In the long term when we arrive at a stabilized 'New Normal', the need to promote public transport is likely to be re-emphasized with high priority. This study presents insights into the factors affecting public transport (PT) preferences and potential modal shifts within various modes of PT when proactive and reactive health control measures are implemented. An online stated preference survey was conducted in Hong Kong, where public buses, public light buses, MTR, and taxis are the popular modes of public transport. The regret-based panel mixed multinomial logit model was applied in this study, aiming to capture individual's regret aversion psychology in the context of the COVID-19 pandemic. The results of our random regret model suggest that travelers generally have lower regrets for the chosen mode when having passenger temperature screening, COVID tracing app, and more frequent disinfection, while seem to be unaware of the in-vehicle air quality. Interaction effects between health control measures and personal characteristics (e.g., age and risk attitudes) were also considered. Trip characteristics, including in-vehicle crowding level, fares, in-vehicle travel time, waiting time at a station, walking time, and trip purpose, were found to influence passengers' choices of travel modes. Policy simulations of possible changes in public transport modal preferences in the presence of various health control measures have also been undertaken. The findings suggest that overall health control measures are appreciated by passengers and do align with promotion of a return to public transport use. However, their effects are quite moderate and should be selectively used for different transport modes. Increasing service frequency can be a promising solution, which reduces crowding and waiting time of passengers using public transport modes, and reduces virus transmission risk. This study contributes to a better understanding of public acceptance and preference toward health control measures in public transport, and call for in-depth cost-benefit analysis in the related fields so that better response can be made in possible future public health crisis.

1. Introduction

The outbreak of COVID-19 has caused unprecedented disruption to life and the economy worldwide. Governments have employed various pandemic containment measures such as lockdowns and travel restrictions, which has led to a huge decline in mobility. Since March 2020, residents in different countries or regions have experienced several waves of the COVID-19 epidemic, and they are now trying to

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* Corresponding author.
E-mail addresses: nicole.chen@kaist.ac.kr (T. Chen), xiaowen.fu@polyu.edu.hk (X. Fu), david.hensher@sydney.edu.au (D.A. Hensher), smzcli@gmail.com (Z.-C. Li), tony.nn.sze@polyu.edu.hk (N.N. Sze).

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adjust their life and work to this ‘new normal’. While people are returning to the transport system, their concern over the risk of catching COVID-19 through the use of public transport remains. Passenger behavior changes are expected, which may contribute to structural changes in urban transport demand amid and post the pandemic. To reduce the risk of virus transmission, various health control measures have been imposed, such as mandatory mask-wearing on public transport. Meanwhile, transport operators have implemented a series of anti-epidemic measures such as providing a QR code for contact tracing application, and improving the cleanliness/hygiene of public transport. The changes in travel experience due to the perceived health risk and health control measures are expected to impose significant impacts on PT preferences of trip-makers. Although COVID-19 is becoming a past and health measures have been partially or fully removed in most cities, a good understanding of such control measures’ implications is still of great importance. Indeed, there were several disease outbreaks before COVID, notably the 2003 SARS, 2005; 2013 avian flu, 2015 MERS etc. WHO has been monitoring potential threats linked to viruses such as Zika, Ebola, monkeypox. Lessons have to be learnt, so that better responses could be made for possible future public health crisis.

This issue is particularly important to Hong Kong, which is a public transport-oriented city with very low private car ownership, owing to its dense population and limited land resources (Legislative Council, 2019). In Hong Kong, public transport is the primary mode for both work-related and non-work trips. The public transport usage rate is the highest in the world, accounting for over 90% of the total passenger trips (Transport Department, 2014; Transport and Housing Bureau, 2017). In comparison, the public transport usage rate was around 60% in Singapore, 70% in Seoul, 50% in Tokyo, 30% in London and New York (Transport and Housing Bureau, 2017). In 2019, there were more than 12 million passenger journeys on public transport every day, which reduced to 8.9 million due to the pandemic in year 2020 (HK Smart City Blueprint, 2021). Through the data analysis of COVID-19 cases, mobility trends, and government responses in Hong Kong, Zhang et al. (2021) found that the mobility trend for public transport is negatively associated with the daily confirmed cases. However, policy adjustments lagged behind the changes in pandemic situation, leading to difficulties in public health control. Overall, residents in Hong Kong showed a willingness to comply with control policies during the pandemic. Still, despite that health control on public transport was designed to help prevent the transmission of COVID-19 and reduce passengers’ perceived travel risk, the resultant inconvenience, privacy concern (e.g., biometric data involved in APP use), and possible increase in monetary costs may significantly change the traffic volume as well as mode choice pattern of the transit users (i.e., passenger trip distribution over different public transport modes).

Therefore, a primary question is - how to maintain the ability of public transport to well serve densely-populated cities (i.e., Hong Kong and other similar major cities around the world), and meanwhile implement essential health control measures despite the possible inconvenience, or increased cost to passengers. One first task is to assess the effects of implementing different health control measures on the mode choice of multiple public transport services. For this purpose, a quantitative analysis is conducted to identify the key factors driving passenger preferences, to better understand passenger transport demand by mode, and to assess possible mode shifts given the implementation of different control policies for public transport in the context of COVID-19. More importantly, by gauging passengers’ preference for the health control measures, this study is expected to provide useful insights into service quality improvements for the public transportation industry, which contribute to the formation of a sustainable new or next normal. For example, the design and implementation of health control measures should achieve a balance between the need of pandemic control and passenger’s travel experience (e.g., convenience, comfort level, reduced risk perception, etc.). Such findings are expected to serve as an important reference to policy makers, since whether to expand the usage of COVID-tracing app or vaccination passport to public transport is a conundrum not only to Hong Kong government but also to other countries or regions (Zhang et al., 2020; Sun et al., 2021). In this study, health control measures are classified into two categories – the “proactive” and “reactive”. Specifically, proactive health control refers to the preventive actions taken to reduce the risk of the transmission of coronaviruses in public transport vehicles. Such measures may include passenger temperature screening, frequent disinfection, and good ventilation of the vehicle. On the other hand, reactive health control refers to the actions taken to deal with the outbreaks when they occur. In particular, the measure of contact tracing for COVID-19 belongs to this category. Such a mobile app provides passengers with rapid notification of exposure to COVID-19 cases, such as the use of “LeaveHomeSafe” mobile app in Hong Kong. This study evaluates the effects of proactive and reactive public health control measures on the passengers’ choices of public transport mode using a stated preference (SP) experiment. The willingness-to-pay estimates for health control measures will also be calculated in the context of COVID-19.

1.1. Problem statement, study objectives, and organization

It is important to note that in the past decades, research has supported the argument that shifting people from private cars to more sustainable modes enhances the health and prosperity of cities. There is, however, recent evidence that suggests a modal shift from shared transportation to private cars during COVID-19 or the post-pandemic world. In this study, we proposed that these findings may not apply to public transport-oriented cities with very low rates of private car ownership, such as Hong Kong. As the ‘new normal’ is established, public transport may introduce health control measures as routine operations as a result of lessons learned during COVID-19. In past research, socio-demographics, trip-related characteristics, and public transport quality were investigated as influence factors on PT mode choice behavior. However, this has rarely been done for the bio-safety issues related to travel. While consideration of these health control factors may be a contribution that seems to be only incremental, it is important to address this gap in the literature because health control measures could become a permanent feature for public transport. This study allows us to obtain quantification of PT preferences and thus predicted traffic volume distributions over PT services.

The remainder of the paper is organized as follows. Section 2 provides a literature review. Section 3 provides a description of the experimental design for data collection, the sample used in the study, and the method of data analysis. The estimation results and policy impact analysis are reported and discussed in Section 4. Finally, Section 5 concludes the paper with a summary of the findings and recommendations.

2. Literature review

As a result of the COVID-19 pandemic and the resulting lockdowns and activity restrictions, the demand for public transport has dropped dramatically in many countries. For example, during the first wave of the COVID-19 pandemic in Australia (i.e., March to April 2020), public transport use decreased drastically by more than 80%, while New York City reported a decline in bus ridership by 97% at around the same time (Beck et al., 2021). In Sweden, the decrease in public transport ridership due to the pandemic was the most severe among all modes, ranging from 40% to 60% across regions (Jenelius and Cebecauer, 2020). In Hong Kong, the ridership of Mass Transit Railway (MTR) during the first wave (end of Jan to March 2020) decreased, on average, by about 50% weekly. Over 60% of Hong Kong residents avoid using public transport on Sunday during the pandemic as they usually have no work-related trips on weekends. Overall, Hong Kong residents perceived a higher infection risk in the MTR trains with poor ventilation and higher occupancy rates, and at crowded stations (Zhang et al., 2021). Similarly, a significant reduction in metro trips in Taipei city took place during the pandemic due to passenger's perceived health risk (Chang et al., 2021). Beck et al. (2021) measured the relationship between the changes in public transport use and bio-security concerns over the three waves of COVID-19 in 2020 in Australia. Their results indicate that people who express greater levels of concern about public transport hygiene are more likely to have zero public transport trips. Shibayama et al. (2021) compared the lockdown experiences and resultant changes in commuting patterns in fourteen countries and found that people change their travel modes from public transport to other modes in order to reduce the risk of catching COVID-19.

In this context, the possible shift from public transport mode to the driving alone mode becomes a major concern since it can lead to more severe traffic congestion and air pollution (due to increased emissions of automobile) (Das et al., 2021). Bhaduri et al. (2020) found that a large proportion of people in India choose the pre-COVID mode as the major mode during the pandemic, while there also exists a high propensity of mode shift from shared ones (e.g., public bus and ridesharing) to private modes (e.g., personal car). Similarly, Abdullah et al. (2020) revealed that people become more sensitive to health risk factors (e.g., infection risk, social distance measures, vehicle cleanliness, mask-wearing requirement for passengers, etc.) and tend to use private cars more frequently during the pandemic while reducing the use of public transport. People generally viewed private car, cycling, and walking as the safest mode during the pandemic due to the lower exposure risk to the coronavirus, while traveling by public buses, metro, taxis, and ride-hailing services are considered risky (Mohammadian et al., 2020). Nevertheless, a significant modal shift from public transport to private mode may not be conceivable in public transport-oriented cities, especially those with low rates of private car ownership. For example, in Hong Kong, statistics show that after the COVID-19 outbreak, the number of private cars registered for the first time has not increased significantly, and the average annual mileage (VKM) per private car has remained fairly stable at around 11,000 km with a mild downward trend (Legislative Council Secretariat, 2022).

There is no doubt that before the influence of COVID is completely removed, health control measures implemented for public transport will remain an important factor in attracting patronage back to public transportation services in a post-pandemic world. Conventional health control measures for public transportation include social distancing, compulsory mask-wearing, pre-boarding temperature screening, cleaning and disinfection of vehicles, and improved ventilation system that brings in sufficient fresh air (Kamga and Eickemeyer, 2021; Zhang J. et al., 2021). In view of the global drop in rail passenger traffic, Vichiensan et al. (2021) conducted a survey targeting railway passengers to gauge their opinions on the countermeasures implemented for Bangkok's urban rail to curb the spread of COVID-19. Their results reveal that passenger temperature screening, requirements of mask wearing, and disinfection of the compartments help increase passengers' confidence in traveling on trains. In addition, respondents showed concerns about the crowding level at railway stations or in a train due to the perceived higher infection risk. Das et al. (2021) revealed that passengers regard certain measures as effective to promote public transport use in the 'new normal', such as reconfiguring bus seats based on appropriate social distancing measures, cleaning and disinfecting buses frequently, restricting the number of passengers on board, and providing real-time information on crowding levels. Yin et al. (2021) evaluated the health control measures implemented for rail transit using different indicators. From the perspectives of effectiveness and economic efficiency, passenger temperature screening and mask wearing can be good choices. Considering the acceptability, travel convenience and comfort level, passengers prefer a control over the loading rate by reducing the crowding level of the train compartments (e.g., restricting the number of passengers onboard to increase the standing area per capita). From the perspective of possible privacy invasion, passengers are sensitive to the collection of their personal identity information and travel record. This calls for a short data storage time to ensure COVID tracing without sacrificing privacy.

Compared with the conventional health control measures, the emerging technologies for contact tracing help prevent the spread of COVID-19 in an effective and rapid manner, while also raising concerns over the issues of associated security risks, ethical and legal risks, privacy invasion, and discrimination (Mbunge, 2020). Zhang et al. (2020) conducted a survey with a sample of two thousand U.S. residents to understand their attitudes toward the health control measures against COVID-19 and found that respondents are more supportive to the requirement of temperature screening in public places but are averse to the use of contact tracing apps. Indeed, previous research revealed that travelers who are privacy-sensitive showed low willingness to share their biometric and behavioral information (Ioannou et al., 2020). Interestingly, similar findings were found for passengers in Western Countries (e.g., U.S., U.K.), where the respondents are more privacy-conscious and sometimes averse to certain pandemic control measures that require personal information (Xing et al., 2021; Zhang et al., 2021). In contrast, passengers from the east are found supportive to contact tracing app (e.g., Thailand, China, see Vichiensan et al., 2021; Xing et al., 2021).

Some recent studies have attempted to study the effects of health screening procedures on air passengers' travel choice (Khatib et al., 2020; Fu et al., 2021), in view of the significant disruptions caused in the aviation industry (Czerny et al., 2021; Tsui et al., 2021; Salesi et al., 2022; Ng et al., 2022). The changes in travel behavior during the pandemic in the context of the urban transport sector have attracted even more attention (such as those referenced earlier). However, these studies either aggregated various public transport modes into one "PT mode", or only investigated the use of one single mode (e.g., metro, bus). In practice it is not uncommon for transport operators to arrange different control strategies depending on the mode of public transport. For example, passengers may need to make a choice between taxi (that requires the use of tracing app) vs. public bus (that requires a passenger temperature check). The limited research on the effects of the proactive and reactive health control measures implemented for different public transport modes (i.e., public buses, public light buses, metro/MTR, and taxi[1]), can be considered as an important gap in the literature.

Furthermore, travel time and crowding level were identified as critical factors affecting the preference for mode shift from public transport to the private car (Das et al., 2021). Previous studies indicated that passengers' discomfort and dissatisfaction increase with the in-vehicle crowding level, which would increase the value of travel time savings (VTTS) (Li and Hensher, 2011, 2013). Li et al. (2017) examined the effects of in-vehicle crowding on the travelers' mode choices and found significant difference in the impacts of in-vehicle crowding on VTTS across different transport modes. However, changes in the valuation of crowding (i.e., WTP to reduce crowding level), as well as its impacts on VTTS and demand estimation are expected. This is because higher passenger density in public transport vehicles also reflect a higher exposure to COVID-19. In such cases, it is likely that passengers' concern about overcrowding mainly comes from the increased risk of catching COVID, rather than the increased travel stress, feelings of privacy invasion, safety, reduced economic productivity, and pickpocketing (identified by precious studies, see Pel et al., 2014; Tirachini et al., 2013).

The synthesis of the literature indicates that (i) recent findings in terms of a significant modal shift from public transport to private mode may not be plausible in public transport-oriented cities; (ii) while recent studies have discretely examined the impact of health control measures on passengers' confidence in traveling on different public transport

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[1] Taxi mode is considered one of the public transport modes in this study. They offer personalized, point-to-point, and more comfortable public transport services at higher rates (Transport and Housing Bureau, 2017).

modes, our understanding remains vague on how these measures would change the behavior of captive transit users; (iii) there is a need to revisit the effects of in-vehicle crowding and mode-specific VTTS in the context of COVID-19 pandemic. In the 'new normal', it is likely that public transport may introduce health control measures as routine operations based on the lesson learnt during the COVID-19 pandemic. A detailed investigation of the decisions regarding the choice of PT mode in the presence of this new permanent feature is missing, which is critical for the prediction of traffic volume distributions over PT services in a sustainable 'new normal'. Therefore, we feel that the stated research gap is very significant, from a practical perspective. The unique contributions include (a) identification of the key factors affecting passenger's PT preferences when reaching a 'new normal'; (b) assessment of possible modal shifts within various PT modes given the implementation of different control policies for public transport; and (c) updates on willingness to pay for improved PT services.

3. Methodology

The data used for the analysis is drawn from a web-based survey conducted from June to July 2021 in Hong Kong. Five hundred and fifty-six participants were selected from an online consumer panel (www.Credamo.com), given sufficient evidence that a representative sample can be delivered through applying proper quota criteria to the established panels (Devarasetty et al., 2012; Mulley et al., 2018; Zheng et al., 2016; Eldeeb and Mohamed, 2020). Instead of a face-to-face interview, an online survey was chosen given the logistics, budget, sampling integrity, and the social distancing policy implemented during the COVID-19 pandemic. As concluded by previous studies, the main drawback of online surveys is the sample bias resulting from non-response of people who have no access to the internet (Iragüen and de Dios Ortúzar, 2004; Zheng et al., 2016). Yet, internet access may not be a significant concern for this study since 92% of the population in Hong Kong are internet users (The World Bank, 2020). On the other hand, the advantages of online surveys, be they base on a consumer panel or other sampled respondent plans, include a reduction in response time and cost, flexibility in providing answers, exemption from decoding and digitizing the responses, the ability to automatically randomize choice sets and scenarios, and capability of pivot design (i.e., customize the survey for individual respondent based on personal experience) (Iragüen and de Dios Ortúzar, 2004; Eldeeb and Mohamed, 2020).

The survey instrument has three sections: (1) Passenger attitudes and travel experience, (2) Stated preference (SP) experiments, and (3) Personal characteristics. The first section collected information on attitudes towards health risk during the pandemic, risk of sharing personal location or providing travel history to mobile apps/websites, and perceived importance of the comfort level inside the traveling vehicle. Respondents are required to rate their level of agreement with each statement on a 7-point Likert scale (1 = strongly disagree; 7 = strongly agree). According to recent research on travel behavior, these items and statements are selected and refined (Chen et al., 2022a, 2022b; Lavieri and Bhat, 2019; Márquez and Poveda, 2019). The attitudinal factors considered in subsequent model formulation are – privacy concern, comfort concern, and health concern. Relevant studies, such as those discussed in the literature review section, suggest that these attitudinal factors may contribute to travelers' preference heterogeneity. Also, their travel habits such as travel partners, days working from home, and usage of public transport before and during the COVID-19 pandemic are obtained. The third section collected information on passengers' socio-demographic characteristics (e.g., gender, age, marital status, income, and living environment).

In this study, an SP approach is adopted since some of the health control measures are not currently implemented for most of the public transport modes (i.e., only taxis provide a QR code for COVID-19 contact tracing; temperature screening devices do not exist in any of the public transport modes; MTR has a clear instruction regarding the disinfection rate of their trains while light bus and taxi drivers clean their vehicles discretionarily). Specifically, the SP design enables the introduction of currently not available alternatives and various combinations of attributes levels, thereby contributing to a wider range of choice scenarios that are not currently observed (Jin et al., 2020). To avoid the situation that respondents do not take the SP experiments seriously, the hypothetical scenarios need to be made as realistic as possible (Hensher et al., 2011, 2015). Strategies proposed by Zheng et al. (2016) to ensure the reliability of SP data such as conducting a comprehensive review of candidate attributes, using pictograms to represent the alternatives and choice scenarios, keeping reasonable survey time/workload, using efficient design, and pivoting off the attribute levels based on the real-life situation, etc., are applied in our experimental design.

3.1. Stated preference design

The conventional design procedure for SP experiments (see Bliemer and Rose, 2006) consists of three steps: model specification (e.g., which alternatives/attributes/model type, etc.), experimental design (e.g., how to set attribute levels, combinations of attribute levels, choice scenarios, etc.), and questionnaire configuration. In this study, passengers' sensitivity towards the effects of proactive and reactive public health control measures was gauged using their stated PT preferences in the SP experiments. The scenarios in the current paper consider two distinct trip purposes: leisure and business. For each question, four PT mode options (i.e., public bus, public light bus, MTR, and taxi) are presented. The attributes and their associated levels were selected based on the latest Travel Characteristics Survey (TCS) in Hong Kong (involving more than 35,000 households, Transport Department, 2014), as well as the evidence found in previous mode choice studies. The findings from TCS have enhanced the understanding of residents' transport mode preferences and provided rich information on the territory-wide travel activities; therefore they have been extensively used in recent studies (Sze et al., 2019; Yang et al., 2021; Xu et al., 2022). TCS revealed that the main factors considered by public transport users when choosing among different modes are travel time and walking distance between trip origin (or, destination) and boarding (or, alighting) location, trip distance, travel cost, waiting time for the public transport service, and degree of comfort. Moreover, in-vehicle crowding discomfort has also been identified as a significant impact factor of passengers' mode choices (Li et al., 2016, 2017), especially when passenger density is correlated with the risk of catching COVID-19 (Lu et al., 2021). In many cities, bicycles have been extensively used as an important transport mode, especially in some Asian cities with the revival of shared bikes. However, cycling constitutes just 0.5% of overall trips in Hong Kong, which is quite low by international standard (Mueller et al., 2018). It is therefore not analyzed in this study. In addition, compulsory mask wearing requirements has been introduced on all public transport modes since the early stage of the pandemic. Therefore, compulsory mask wearing is not separately controlled neither.

Based on the extensive review of relevant literature, government reports, the current anti-epidemic efforts, and a pilot survey, a list of the selected attributes is shown in Table 1. In each of the presented choice scenarios, two categories of attributes are used to characterize the alternatives: (1) public health control measures (including proactive and reactive measures), and (2) travel characteristics (including the total walking time, waiting time at station, in-vehicle travel time, fare, and in-vehicle crowding).

The levels of the attributes – time interval of disinfection – were set based on an interview with public light bus and taxi drivers (mostly self-employed, not regulated by a company), and the review of infection control measures adopted by franchised bus companies and metro operators (KMB, 2020a; MTR, 2020). The disinfection and cleaning of the compartments for the public bus and MTR are in general every 60 and 45 min, respectively. We used these disinfection rates (i.e., time

Table 1

Stated preference experimental design: attributes and levels.

Attributes		Public bus	Public light bus	MTR	Taxi
Public health control measures					
Proactive measures	Time interval of disinfection	per 0.75 h (per 45 min)/ per hour/ per 1.5 h/	per hour/ per 1.5 h/ per 2 h	every half an hour/ per 0.75 h/ per hour	per hour/ per 1.5 h/ per 2 h/
	Air exchange rate of the compartment	2/4/6 times per hour	0.5/1/2 times per hour	3/6/12 times per hour	1/3/5 times per hour
	Temperature screening	Yes/No requirements	Yes/No requirements	Yes/No requirements	Yes/No requirements
Reactive measures	Provide a contact tracing QR code to record a visit	Yes/No	Yes/No	Yes/No	Yes/No
In-vehicle travel time (minute)	Short trip	5, 10, 15	5, 10, 15	5, 10, 15	5, 10, 15
	Medium trip	15, 25, 40	10, 15, 20	15, 25, 40	10, 15, 20
	Longish trip	40, 50, 60	20, 30, 40	40, 50, 60	20, 30, 40
Fare (HKD)	Short trip	4, 6	5, 10	4, 6	25, 40
	Medium trip	6, 10	10, 15	6, 10	40, 80
	Longish trip	15, 25	20, 30	15, 25	80, 120
Total walking time (minute)		5, 10, 15	5, 10, 15	5, 10, 15	1, 3, 5
Waiting time at station (minute)		4, 8, 12	3, 5, 10	2, 4, 6	0, 3, 6
Crowding level (i.e., Percentage of seats[a] occupied at time of boarding)		10%, 50%, 90% (Max: 130 passengers)	10%, 50%, 90% (Max: 19 passengers)	10%, 50%, 90% (Max:280 passengers/car)	–

Note:

[a] The presentation of crowding on MTR trains in this study refers to the percentage of car capacity.

interval) as the status quo and also introduced a higher and a lower disinfection level for both public bus and MTR. On the other hand, the interviewed taxi and public light bus drivers indicated that vehicle disinfection is not mandatory, yet they usually do it every one to 2 h. Therefore, three levels of this attribute for taxi and public light bus are set as: disinfecting the passenger compartment every 1, 1.5, and 2 h.

The levels of the air exchange rate of the compartment were set based on the vehicle types. Sun and Zhai (2020) conducted an extensive review on design standards by public transport vehicle types and evaluated the association between the COVID-19 infection risks and the parameters of air exchange rate and passenger capacity. MTR trains compartments continue to reach Level 1 air quality, which is the highest level under the practice note issued by Environmental Protection Department (Transport and Housing Bureau, 2019). Yet, government experts suggested that when the MTR train reaches half of its passenger capacity, the air exchange rate of the compartments should be at least six times per hour to provide fresh air and reduce the risk of COVID-19 transmission. Also, the air exchange rate should be increased if there are more passengers on board (The Government of HKSAR, 2020). Therefore, we used six times per hour as a medium level, and introduced a decreased level (i.e., three times per hour) and an increased level (twelve times per hour) for the MTR mode. Even though the franchised bus company has adopted measures to increase ventilation in the bus compartment so as to reduce the infection risk (KMB, 2020b), previous experience shows the air quality in buses may not be as good as that in MTR trains (Transport and Housing Bureau, 2013). The vehicle design standards show that the ventilation rate is usually higher for metro compared to public buses (Sun and Zhai, 2020). Also, considering the difference in passenger capacity between public buses and MTR trains (e.g., a maximum of 130 passengers for the double-decker bus vs. a maximum of 280 passengers per car of the MTR train), we set six times per hour to be the highest level of air exchange rate for the public bus mode, and introduced two decreased levels (i.e., two and four times per hour). As for public light buses and taxis, drivers expressed concern about the increased petrol costs due to the use of air conditioning and ventilation systems. Our interview revealed that public light bus drivers on average switch on the vehicle ventilation system from the recirculation mode to the fresh air mode about once per hour, while taxi drivers would do it when a new passenger gets on board. As taxi trips on average were about 24 min (Transport Department, 2014), we used three times per hour as a medium level, and introduced a decreased level (i.e., once per hour) and an increased level (five times per hour) for taxi mode. The levels of the air exchange rate for public bus mode are set as: once every 2 h, once per hour, and twice per hour.

We also included “Yes” and “No” levels for the presence of temperature screening (third attribute) and contact tracing QR code (fourth attribute). These two attributes are available only in the SP scenarios, as temperature screening is currently available for drivers and air passengers (Chen et al., 2022a, 2022b). Moreover, contact tracing QR Codes are provided on 18,000 taxis and at about 200 bus terminals and interchanges, while the use of QR code will be piloted on public light buses in Hong Kong soon (Wong, 2021).

To generate meaningful trips, three “distance” scenarios – short, medium, and longish trips – were designed using sensible values of travel time and the corresponding ticket fare. The travelers’ responses collected by TCS were used to determine realistic attribute levels for total walking time, waiting time at station, in-vehicle travel time, and fare (Transport Department, 2014). Specifically, the total travel time (i.e., from trip origins to destinations) of more than 50% of the mechanized trips were less than 30 min and that of 90% trips were less than an hour. While taxi trips on average took a journey time of approx. 24 min, the public transport (excluding taxi) trips on average took a journey time of 43 min. In this context, the values set for in-vehicle travel time should be overall reasonable. In addition, more than 75% of Hong Kong residents can access a public transport mode within a 5-min walk (or from the alighting point to their destination). Thus, the medium level of total walking time was set to be 10 min for access and egress connection to transit services. The levels of the walking time to reach a taxi stand were set to be 1, 3, 5 min, as taxi passengers would arrive at their destination directly. The stated maximum acceptable waiting time varied by public transport services, ranging from 6 to 12 min (i.e., 6 min for MTR and Taxi, 10 min for public light bus, and 12 min for public bus). In-vehicle crowding is defined based on the approach proposed by Hensher et al. (2011) and applied in many previous studies (e.g., Tirachini et al., 2013; Ho et al., 2020), in which crowding on public transport is presented by the percentage of seats occupied at the time of boarding (i.e., 10%, 50%, 90%). Respondents raised concerns on this definition of crowding levels on trains, because trains in Sydney offers more seats but a smaller standing area while the MTR trains in Hong Kong rely more on the standing area (e.g., 280 passenger capacity per car with only 52 seats). Therefore, the presentation of crowding on MTR trains in this study was revised as – the percentage of design loading (6 person per m^2), which is easier to comprehend and meanwhile consistent to the conventional indicators used in government reports (Legislative Council, 2015).

The levels used for each of the attributes in the SP experiment were tested extensively in a pilot survey to ensure their readability, reasonability, and simplicity. Overall, the SP experiments include 9 attributes as presented in Table 1, in which 6 with three levels and 3 with two levels. To generate the combinations of attribute levels for the choice scenarios, we applied a Bayesian efficient design that aims to generate parameter estimates with as small as possible standard errors, instead of an orthogonal design that aims to minimize the correlations between attributes and which typically requires a much larger sample. In this study, D-error is deployed to measure the efficiency of the design, in which the parameter estimates of the preliminary model (using the data collected from the pilot survey that applied orthogonal design) were used as priors (Eldeeb and Mohamed, 2020; Hensher et al., 2011; Li et al., 2017; Mulley et al., 2018; Rose et al., 2008; Zheng et al., 2016). The software package *Ngene 1.2* (ChoiceMetrics, 2018) is used to generate the choice scenarios. In total, the number of scenarios generated was set to 48, which was determined by the number of alternatives (Alt) and the total number of parameters to be estimated (K). Based on the user manual (ChoiceMetrics, 2018), the number of scenarios generated should be no less than K/(Alt - 1), therefore 48 choice scenarios are sufficient for our study. Since it is infeasible to present 48 SP scenarios to each respondent, we adopted a block design which resulted in six SP scenarios grouped into eight blocks. Each of the participants was randomly given one of the eight blocks of six scenarios, and was required to choose from four labelled mode alternatives as shown in Fig. 1.

3.2. Survey data

556 respondents completed the survey, representing 3336 (556 × 6) valid choice observations. A screening question is displayed at the beginning of the questionnaire to exclude those who own a car and do not use public transit as the main mode of travel. Three methods – response time control (e.g., minimum time period to complete the questionnaire), additional screening questions to test respondents' attention (e.g., "please select five as the answer for this question"), and earnestness of respondents (e.g., one selected the same mode in all SP scenarios within a short time) were used to exclude invalid responses (Li et al., 2017; Fu et al., 2021). Socio-demographic characteristics of the samples in comparison to the population are summarized in Table 2. The gender distribution of the participants of this study is generally consistent with the population census dataset. Despite that, the younger respondents (below 35) showed a slightly higher proportion, but the age distribution of our sample is close to that of the official statistics. In terms of marital status, 47.3% of the respondents were married. Respondents were classified into three monthly income categories: lower income (i.e., below HK$20,000), middle income (i.e., HK$ 20,000–49,999), and higher income (i.e., HK$ 50,000 and above), which occupied 52.7%, 40.1%, and 7.2%, respectively (the distribution is comparable to the monthly wage distribution of all employees in Hong Kong). For the perception variables, 28.4% of the respondents perceived higher health risk during the pandemic, while 12.4% expressed lower health concerns. As for the perception on the risk of providing location/travel history information online, 16% of the sample express higher privacy concern, while a smaller percentage (2.3%) believed that the associated risk is low. 25.2% of the respondents viewed the comfort level inside the vehicle as very important, while the other respondents attach medium or lower importance to in-vehicle comfort.

The distribution of public transport use frequency before and during the COVID-19 pandemic is shown in Table 3. Before the pandemic, MTR

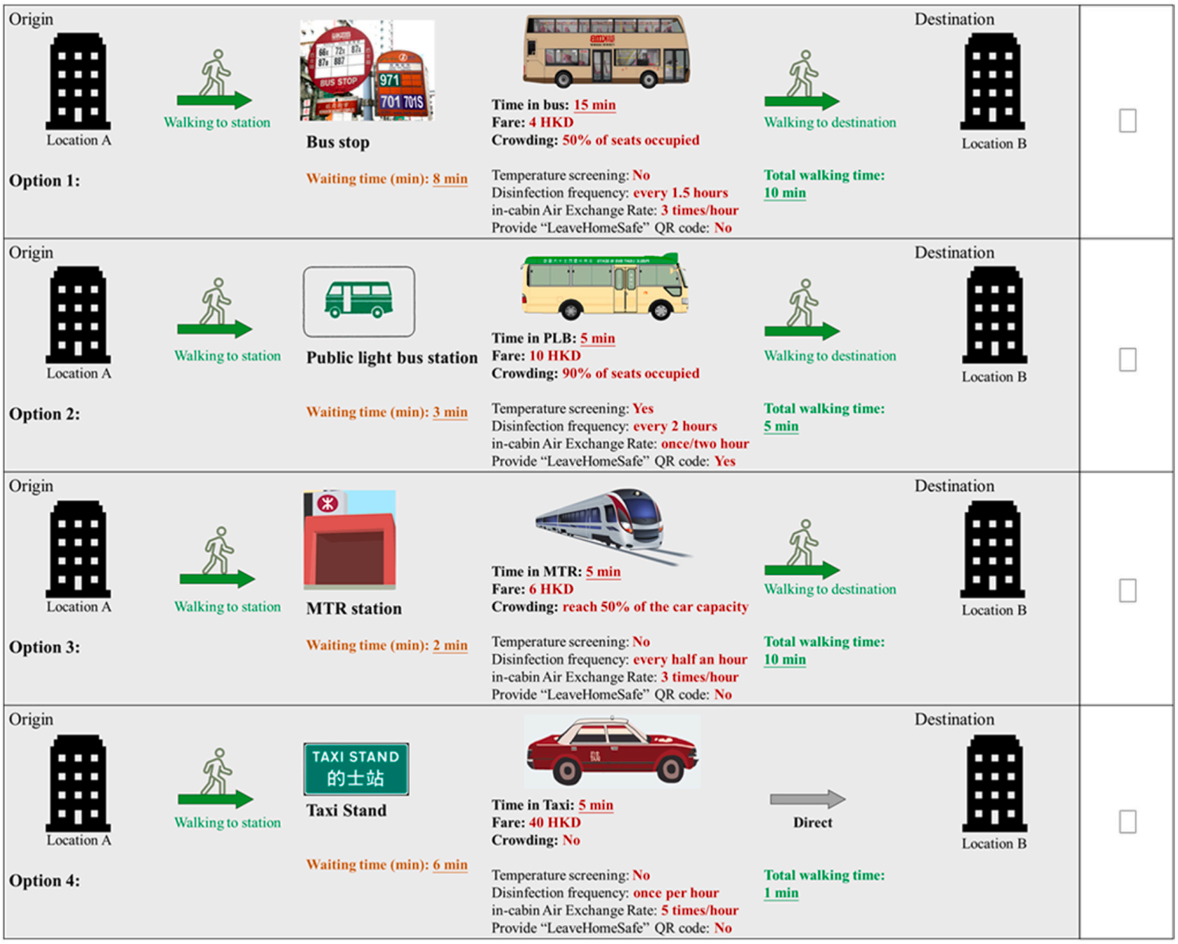

Fig. 1. Example of a mode choice scenario.

was the most popular transport mode followed by public bus, while taxi and public light bus (PLB) accounted for approx. 16% of the total boardings. This distribution is generally consistent with the TCS report (Transport Department, 2014). After the outbreak of COVID-19, most of the frequent taxi riders still chose taxi for travel. For those who used to travel by public buses, about one third of them shifted to the taxi mode during the pandemic. In addition, while about 22% of the respondents who stated to travel by PLB mostly kept their original choice during the pandemic, more than 40% of them shifted to a taxi mode. Likewise, while about 30% of MTR enthusiasts have not changed their most frequent mode of travel, nearly 40% chose to travel by a taxi during this critical period.

3.3. Model specification

As an alternative to Random Utility-Maximization (RUM) models, the Random Regret-Minimization (RRM) model was used in this study. Regret Theory is the theoretical basis for RRM models, which enables the analysis of travel demand with several useful features (Chorus et al., 2008; Chorus, 2010; Chorus and Bierlaire, 2013; Hensher et al., 2013). This model has the advantage of allowing decisions between travel alternatives to be motivated by avoiding negative emotions rather than maximizing rewards. A further benefit of this model is that it acknowledges that decision-making by travelers may not be fully compensatory when faced with multi-attribute alternatives (Chorus et al., 2008). Indeed, RRM models can capture the loss aversion psychology of individuals, which attracts scholars to apply them to emergency situations or the context of risky choice analysis (Chorus, 2012; Wang et al., 2018; Wong et al., 2020). These studies revealed that RRM models show a better performance to capture individual's regret aversion psychology. In the context of the COVID-19 health crisis, fear and uncertainty about infection risk arise, causing regret aversion psychology to drive the decision-making of travel mode choice (Xiao et al., 2023).

The proposed regret-based model includes the following features. First, random-parameter model is adopted to accommodate taste heterogeneity across the sample assuming a normal distribution. Second, the panel effect is also addressed through the recognition of the correlations among the repeated choices made by the same respondent. We assume a sample of Q decision-makers who are required to choose among J mode alternatives in S choice scenarios. A total of K attributes are used to describe the alternatives. For choice *j*, the systematic regret is R_j, which is defined as the sum of the binary regrets resulting from bilateral comparisons of kth attributes of the chosen alternative and other viable alternatives *i*. In comparison to available alternative *i*, the attribute-level regret for alternative *j* is (Chorus et al., 2008; Chorus, 2010),

$$R_{ji(k)} = ln\left\{1 + exp\left[\beta_k\left(x_{ik} - x_{jk}\right)\right]\right\} \tag{1}$$

Then, the random regret for alternative *j* in scenario *s* of individual *q* is,

$$\mathrm{RR}_{qjs} = \sum_{i\neq j}\sum_{k=1}^{K} ln\left\{1 + \exp\left[\beta_k\left(x_{qisk} - x_{qjsk}\right)\right]\right\}\varepsilon_{qjs} \tag{2}$$

Table 2
Profile of respondents (N = 556).

Variable	Percentage (%)	Population (%)	
Demographics		Official Categorization	
Gender		(Census and Statistic Department, 2021)	
Male	46.2%	Male	45.6%
Female	53.8%	Female	54.4%
Age		(Census and Statistic Department, 2021)	
18–25	15.1%	15–24	8.2%
26–35	26.9%	25–34	13.5%
36–45	18.5%	35–44	15.8%
46–55	12.3%	45–54	15.1%
56–65	14.1%	55–64	16.5%
Above 65	13.1%	65 and 65+	19.3%
Marital Status		(Census and Statistic Department, 2021)	
Married	47.3%	Married	58.4%
Single	52.7%	Never married	29.4%
–		Widowed/ divorced/ separated	12.2%
Current Monthly Income		(Census and Statistic Department, 2020)	
Below HK$ 20,000 (Lower income level)	52.7%	50th percentile	HK$ 18,400
HK$ 20,000–29,999	19.6%	75th percentile	HK$ 28,800
HK$ 30,000–39,999	11.9%	90th percentile	HK$ 45,300
HK$ 40,000–49,999	8.6%		
HK$ 50,000 and above	7.2%		
Attitudes# (1–7 Likert scale)			
Perceived risk of giving location/ travel history information to mobile apps/websites			
High (>5 points, Privacy Concern)	16.0%	–	N/A
Medium (4–5 points)	81.7%	–	N/A
Low (1–3 points)	2.3%	–	N/A
Perceived health risk during the pandemic			
High (>5 points, Health Concern)	28.4%	–	N/A
Medium (4–5 points)	59.2%	–	N/A
Low (1–3 points)	12.4%	–	N/A
Perceived importance of the comfort level inside the vehicle			
High (>5 points, Comfort Concern)	25.2%	–	N/A
Medium (4–5 points)	73.6%	–	N/A
Low (1–3 points)	1.3%	–	N/A

Note: the attitudinal statements include – (a) "I believe that in giving my location/travel history information to mobile apps/websites: the risk involved is high"; (b) "Traveling by public transport will increase health risks based on the lessons learnt during the pandemic"; (c) "The carriage should be neat and tidy, and the crowdedness inside makes me uncomfortable".

Table 3
Public transport usage frequency before and during COVID-19.

The most frequent PT mode choice before COVID-19		The most frequent PT mode choice during COVID-19				
	Count (%)	Taxi	Public Bus	PLB	MTR	Others
Taxi	51 (9.17%)	29 (56.86%)	4 (7.84%)	0 (0.00%)	5 (9.80%)	13 (25.49%)
Public Bus	113 (20.32%)	40 (35.40%)	27 (23.89%)	9 (7.96%)	15 (13.27%)	22 (19.47%)
PLB	36 (6.47%)	15 (41.67%)	4 (11.11%)	8 (22.22%)	2 (5.56%)	7 (19.44%)
MTR	325 (58.45%)	129 (39.69%)	16 (4.92%)	24 (7.38%)	98 (30.15%)	58 (17.85%)
Others	31 (5.58%)	4 (12.90%)	0 (0.00%)	0 (0.00%)	2 (6.45%)	25 (80.65%)

Note: "Others" including Light Rail Train (LRT), Tram, and Ferry, accounted for 3%, 2%, and 1% of the total boardings respectively in 2011 survey (Transport Department, 2014).

$$\beta_k = \beta_k^{'} + \omega_q \tag{3}$$

where x_{qjsk} denotes the value of kth attribute of chosen alternative j and x_{qisk} denotes that of the other alternative i. β_k is the normal distributed random parameter with a mean vector of $\beta_k^{'}$ (that is, the coefficient of kth attribute). ω_q refers to an independently and normally distributed random error term, with zero mean and variance σ_w^2, demonstrating the impact of unobserved individual heterogeneity. If the variance of β_k is statistically significant at the 5% level, the parameter is set to random, otherwise it is fixed. ε_{qjs} refers to an identically and independently Gumbel distributed error term.

The probability that individual q will choose alternative j on the sth choice scenario is derived using a variant of the multinomial logit (MNL) formulation (Chorus et al., 2008; Chorus, 2010):

$$P_{qjs} = \frac{\exp(-\mathrm{RR}_{qjs})}{\sum_{j=1}^{J}\exp(-\mathrm{RR}_{qjs})} \tag{4}$$

For more details on RRM models, please refer to Chorus et al. (2008), Chorus (2010, 2012), and Hensher et al. (2015). The maximum (log) simulated likelihood (MSL) estimator is used to estimate the parameters in the proposed RRM model. The detailed estimation process for RRM models has been reviewed and demonstrated in recent behavioral studies (see Iraganaboina et al., 2021; Zhu et al., 2021). The software package *NLOGIT 6.0* is used to estimate the proposed random-parameter random regret model (equivalent to, a regret-based panel mixed multinomial logit model).

3.4. Trade-off analysis

The following is a description of the methodology used in our trade-off analysis. In this study, these trade-offs are estimated: (i) trade-off between time (including walking time, in-vehicle travel time, and waiting time at station) and travel cost, and (ii) willingness to pay (WTP) for the health control measures.

In Chorus (2012), the differing trade-off formulations between RRM's MNL model and RUM's linear-additive MNL model are examined in detail. It should be noted that, the trade-offs are dependent on the attribute levels in the random regret framework. As such, the trade-off between time and travel cost (value of travel time) in an RRM model is given by (Chorus, 2012):

$$VoT_j = \frac{\partial RR_j / \partial TT_j}{\partial RR_j / \partial TC_j} = \frac{\sum_{i \neq j} -\beta_{j,TT} \Big/ \left(1 + \frac{1}{\exp\left[\beta_{j,TT}\left(TT_i - TT_j\right)\right]}\right)}{\sum_{i \neq j} -\beta_{j,TC} \Big/ \left(1 + \frac{1}{\exp\left[\beta_{j,TC}\left(TC_i - TC_j\right)\right]}\right)} \tag{5}$$

Using equation (5), we can further transform it into the following equation:

$$VoT_j = \frac{\partial RR_j / \partial TT_j}{\partial RR_j / \partial TC_j} = \frac{\beta_{j,TT}}{\beta_{j,TC}} \frac{\sum_{i \neq j} \exp\left[\beta_{j,TT}\left(TT_i - TT_j\right)\right] \Big/ \left(\exp\left[\beta_{j,TT}\left(TT_i - TT_j\right)\right] + 1\right)}{\sum_{i \neq j} \exp\left[\beta_{j,TC}\left(TC_i - TC_j\right)\right] \Big/ \left(\exp\left[\beta_{j,TC}\left(TC_i - TC_j\right)\right] + 1\right)} \tag{6}$$

where $\beta_{j,TT}$ and $\beta_{j,TC}$ are estimates of travel time and travel cost (fare) for the chosen travel mode j, respectively. TT_i and TT_j denotes the in-vehicle travel time attribute for the considered travel mode i and the chosen travel mode j, respectively. TC_i and TC_j denotes the travel cost (fare) attribute for the considered travel mode i and the chosen travel mode j, respectively.

Further, we incorporate the interaction terms into the fundamental trade-off expression based on equation (5). Then, the WTP for kth attribute for the j can be formulated as:

$$WTP(k)_j = \frac{\sum_{i \neq j} -\beta_{jk} \Big/ \left(1 + \frac{1}{\exp\left[\beta_{jk}\left(x_{ik} - x_{jk}\right)\right]}\right) + \sum_m \left(\sum_{i \neq j} -\beta_{jk}^{m} X_m \Big/ \left(1 + \frac{1}{\exp\left[\beta_{jk}^{m} X_m \left(X_m x_{ik} - X_m x_{jk}\right)\right]}\right)\right)}{\sum_{i \neq j} -\beta_{j,TC} \Big/ \left(1 + \frac{1}{\exp\left[\beta_{j,TC}\left(TC_i - TC_j\right)\right]}\right) + \sum_l \left(\sum_{i \neq j} -\beta_{j,TC}^{l} X_l \Big/ \left(1 + \frac{1}{\exp\left[\beta_{j,TC}^{l} X_l \left(X_l TT_i - X_l TT_j\right)\right]}\right)\right)} \tag{7}$$

where x_{ik} and x_{jk} denotes the value of kth attribute for the considered travel mode i and the chosen travel mode j, respectively. β_{jk} is the coefficient estimates of kth attribute, X_m is the interaction variable to the kth attribute, and β_{jk}^{m} is the coefficient estimate of the interaction term (kth attribute × mth variable) for the chosen mode j. X_l is the possible interaction variable to travel cost, and $\beta_{j,TC}^{l}$ is the coefficient estimate of the interaction term (travel cost × l th variable) for the chosen mode j. The trade-off between travel cost and walking time/waiting time, and WTP estimates for the health control measures can also be calculated by using the same formulations as presented in equations (5) or (6), accomplished by replacing the travel time parameters with attributes of health control measures. However, if there are any significant interaction terms identified, the trade-off/WTP should be computed using equation (7).

4. Estimation results and discussion

4.1. Model estimation

In this study, a random-parameter random regret model based on the multinomial logit formulation is applied to examine the association between attributes (including the health control measures, trip characteristics) and the mode choice of multiple public transport services. Other variables considered in the model include sociodemographic and attitudinal variables (i.e., age, income level, privacy concern, perceived importance of comfort level, and perceived health concern). In the final specification of the RRM model, variables that were found not significant at the 90% confidence level were removed in a systematic process. Also, in the development of the model, any interactions between attributes and other factors (such as personal characteristics and trip purpose) were considered. For the final model, only the interaction terms statistically significant at 90% confidence levels were included.

Table 4 presents the results estimated on the 3336 observations – with normal distributed random parameters.[2] Considering the substantial increase in Log-likelihood, the proposed methodology can be considered valid for regret-based model specification (Chorus et al., 2008; Zhu et al., 2021). Note that the interpretation of the parameter estimates in the random regret model is not equivalent to those in a RUM-model (Chorus et al., 2008; Chorus, 2012). For example, the estimated negative value of travel time parameter implies that the increase in time-difference $(TT_i - TT_j)$ between alternatives (i.e., the considered travel mode i and the chosen travel mode j) potentially reduces regret to the chosen alternative, for the average traveler. A positive parameter, on the other hand, indicates that potential regret increases when the considered alternative outperforms the chosen alternative on this attribute.

In accordance with the mode-specific constants, traveling by PT_shared modes (MTR, bus, and/or PLB) are intrinsically preferable to traveling by taxi. Yet, the preference for PT_shared modes would be reduced significantly for business trip. As for the health control measures, a positive coefficient of passenger temperature screening before boarding indicates a positive impact on minimizing the potential regret for all travel modes. The coefficient for the time interval of disinfection, is negative as expected, indicating a lower regret of people towards a more frequent disinfection (i.e., shorter time interval) of bus and PLB modes. Yet, such effect is not statistically significant for MTR and taxi modes. Interestingly, the parameter estimate for service improvement in terms of the air exchange rate is not statistically significant, while the intersection term (Health sensitive × AER) is significant for the MTR mode. Specifically, for the respondents who perceive higher health risk, increased AER appear to cause a marginal extra decrease in potential regret to the MTR mode. There is no significant evidence for the mean effects of AER on travelers' potential regrets to the chosen travel mode. Indeed, air exchange rate of the vehicle compartment is a "invisible" health control measure. One possible explanation is the relationship between the visibility and the perceived effectiveness of the control measures. In the field of psychology, there is a body of literature to support the argument that people had difficulty evaluating the effects of invisible support (Bolger et al., 2000; Girme et al., 2013). Steinka-Fry et al. (2016) indicated that in United States, many schools implement visible security measures such as cameras and security personnel in order to create a safe learning environment. Often, visible security measures are perceived as necessary and adopted widely, as they serve as physical markers of security and safety (Tanner-Smith et al., 2018; Steinka-Fry et al., 2016). In this study, temperature screening, disinfecting the vehicle, and contact-tracing QR code can serve as physical markers of bio-security/safety.

As for the reactive health control measure, potential regrets can be reduced when the chosen alternative has a contact tracing QR code to record their travel history. However, the use of a contact tracing QR code appears to cause an increase in potential regrets to PT_shared modes for the travelers with higher privacy concerns, as well as an increase in regrets among individuals over the age of 65 regarding their choice of taxi mode.

Table 4
Results of radom parameter random regret model.

Attributes	Mode-specific	Coeff.	Z-stat
$ASC_{\_bus}$	Bus	0.645	3.46
$ASC_{\_PLB}$	PLB	0.651	3.19
$ASC_{\_MTR}$	MTR	0.796	4.83
$ASC_{\_Taxi}$	Taxi *(reference)*	–	–
Health Control Measures			
Temperature screening	All mode	0.140	5.00
		0.256 (sd)	*4.92*
Time interval of disinfection	Bus & PLB	−0.131	−2.29
		0.231 (sd)	*7.90*
	MTR, Taxi	IS	IS
Air exchange rate of the compartment (AER)	All mode	IS	IS
Provide a contact tracing QR code	PT_shared (MTR, Bus, PLB)	0.100	3.19
		0.250 (sd)	*5.52*
	Taxi	0.174	3.48
Trip Characteristics			
Crowding in the vehicle	Bus	−0.854	−8.07
		0.533 (sd)	*4.86*
	PLB	−0.615	−9.30
	MTR	−0.587	−7.85
cost	PT_shared (MTR, Bus, PLB)	−0.023	−4.92
		0.031 (sd)	*8.27*
	Taxi	−0.007	−7.41
Walking time	all	−0.040	−11.45
		0.035 (sd)	*7.69*
In-vehicle travel time	Bus	−0.014	−7.85
	PLB	−0.010	−3.26
	MTR	−0.015	−9.43
	Taxi	−0.018	−5.34
Waiting time at station	Bus & PLB	−0.018	−2.43
	MTR	IS	IS
	Taxi	−0.033	−3.53
Business trip	PT_shared (MTR, Bus, PLB)	−0.883	−10.57
Personal Characteristics			
Comfort sensitive	PT_shared (MTR, Bus, PLB)	−0.105	−2.27
Lower income	PT_shared (MTR, Bus, PLB)	0.235	5.56
Interaction Effects			
Privacy × QR code	PT_shared (MTR, Bus, PLB)	−0.151	−2.15
Business × Waiting time	Bus & PLB	−0.024	−2.56
Business × Crowding	MTR	−0.282	−2.27
Health sensitive × AER	MTR	0.013	1.86
Elderly (65+) × QR code	Taxi	−0.558	−1.97
Goodness of fit measures:			
Number of cases	3336		
Number of parameters	36		
Log-likelihood of constants only model	−4467.27		
Log-likelihood at convergence	−3891.14		
Bayesian Information Criterion	8074.33		

Note: sd denotes random parameters;
IS denotes statistically insignificant.

Moreover, decisions regarding the choice of PT mode are expected to be influenced by a variety of trip characteristics. The characteristics considered include the crowding level of the vehicle, travel cost, walking time, in-vehicle travel time, and waiting time at the station. The coefficient for crowding level shows a negative impact on minimizing the potential regret for the bus, PLB and MTR modes, suggesting greater regrets regarding the increasing crowdedness of the chosen vehicle. Besides that, higher crowding levels appear to cause a substantial additional amount of regret associated with MTR travel for business trips (Business × Crowding). As for travel cost, a negative coefficient indicates reduced regrets towards lower ticket prices, with PT_shared

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[2] Despite exploring alternative distributional assumptions, such as log-normal for the random parameters, the model with a normal distribution provides the best fit. Furthermore, other distributions did not provide substantive interpretations that were very different from those of the model based on normal distributions.

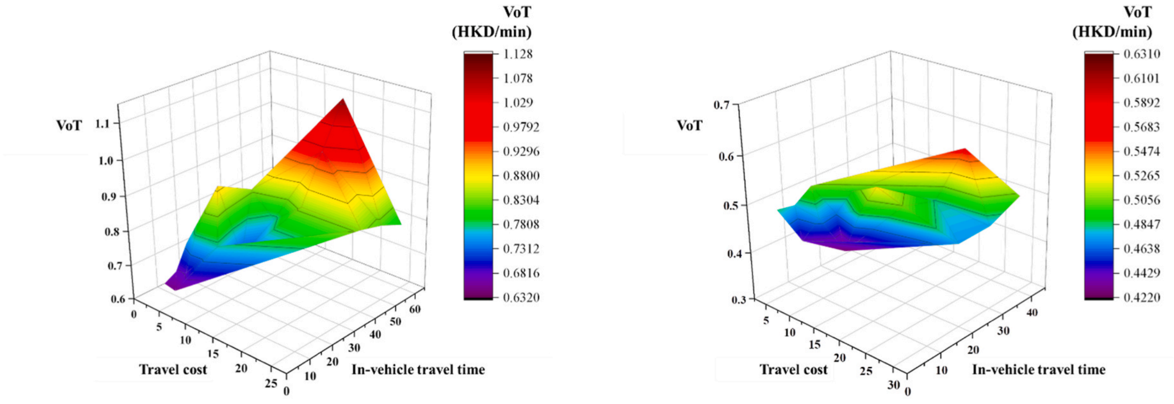
modes having a stronger impact compared to taxi.

The variable of total walking time refers to the time required to access and egress transit services. The coefficient estimate confirms that potential regret increases when the non-chosen alternative requires shorter walking time. For in-vehicle travel time, negative coefficients were found for bus, PLB, MTR, and taxi modes, suggesting a greater regret when the non-chosen alternative has shorter in-vehicle travel time. Particularly, the impact of in-vehicle time is relatively stronger on the taxi mode than on the PT_shared modes. Further, increased waiting times at bus or PLB stations, as well as at taxi stands, contribute to the increase in regrets associated with the chosen alternative, whereas no significant impact is found on the MTR mode. This might be due to the indoor waiting area on MTR train platforms, which offers passengers a more comfortable environment. Aside from that, increased waiting times at stations tend to add a significant amount of regret to the choice of traveling by bus or PLB for business purposes (Business × Waiting time).

Finally, for those who are sensitive to in-vehicle comfort level, tend to have higher regret when choosing the PT_shared modes. In contrast, travelers with a lower income level show a stronger preference for traveling by PT_shared modes. At the same time, the model estimates also recognize statistically significant random parameters for temperature screening, disinfection of bus and PLB, use of contact-tracing QR code on PT_shared modes, crowding level on bus, travel cost for PT_shared modes, and walking time, demonstrating heterogeneous effects of these attributes across the sample population, respectively.

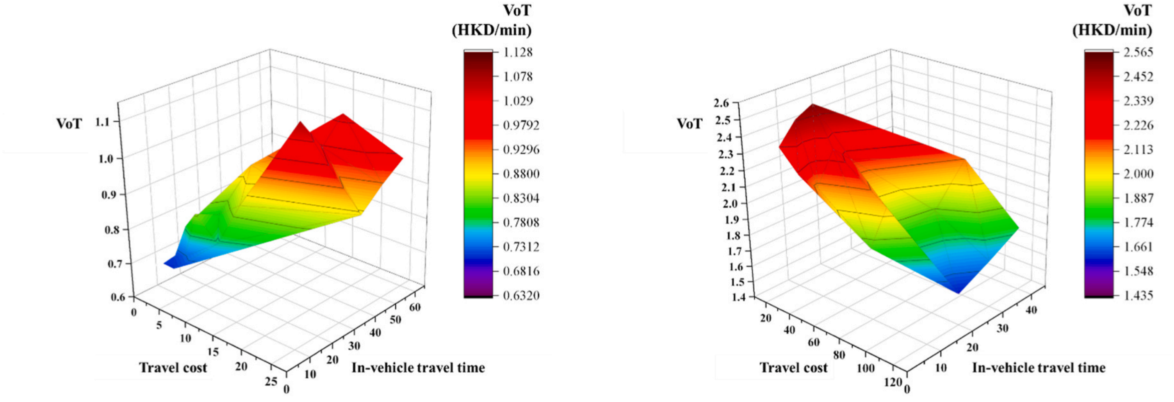
4.2. *Willingness to pay*

The numerical levels of the parameter are not strictly informative given the non-linear form of the model; however, willingness-to-pay estimates are behaviorally meaningful and comparable. Note that based on the discussion by Chorus (2012), the RRM formulation results in alternative- and choice-set-specific trade-off/WTP measures are in contrast to the RUM formulation. Specifically, the travel times and costs for both the considered alternative and its competitors enter the trade-off equation, and thus the trade-off measures based on RRM will generally change when the choice set changes (i.e. alternatives' performances on two attributes in trade-off analysis). Fig. 2 illustrates the results of value of in-vehicle travel time (VoT). As shown in Fig. 2, VoT on bus and MTR varies from 0.62 to 1.13 HK$/min, whereas on PLB it ranges from 0.42 to 0.63 HK$/min. The VoT on taxi is higher compared with other modes, ranging from approx. 1.44 to 2.57 HK$/min. Indeed, previous studies also revealed that taxi users in general have a higher value of travel time savings compared with bus and metro users (Tsamboulas and Nikoleris, 2008; Yang et al., 2014; Kirtonia and Sun, 2022). Overall, the PT_shared modes including bus, PLB and MTR share similar pattern, suggesting that the VoT is higher when the chosen travel mode is relatively cheap but slow, while it becomes lower when the chosen travel mode is relatively fast but expensive. This is intuitive because the results are consistent with RRM's semi-compensatory behavior Chorus (2012). For instance, if a chosen mode is fast but expensive, that means its performance is poor in terms of cost but excels in terms of travel time. In this regard, an increase in travel costs would result in a remarkable increase in regret, while a decrease in travel time would only contribute to a small amount of reduction in regret.



(a) VoT for Bus based on RRM

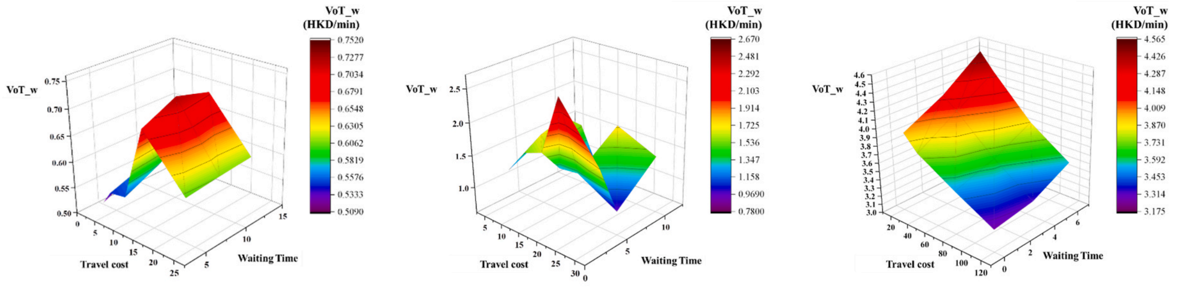
(b) VoT for PLB based on RRM



(c) VoT for MTR based on RRM

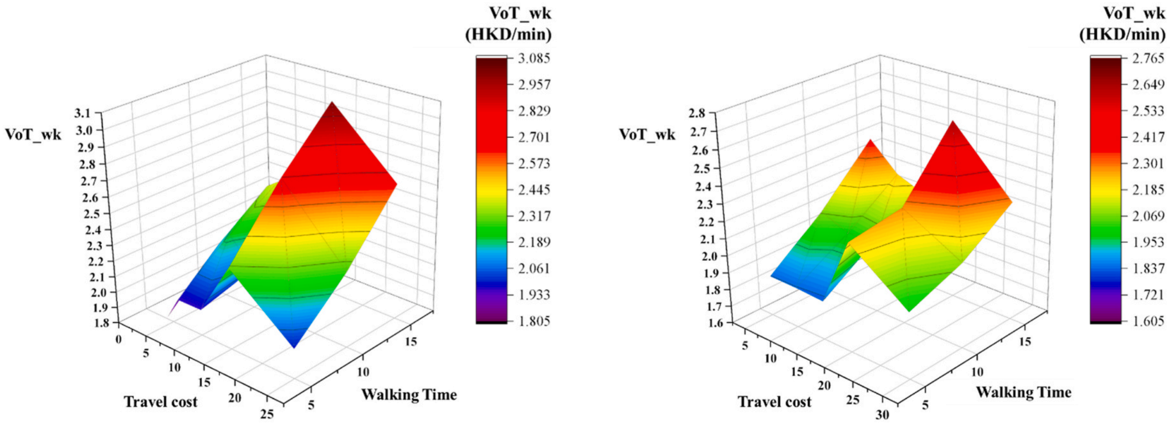
(d) VoT for Taxi based on RRM

Fig. 2. Values of in-vehicle travel time based on RRM across different PT modes.

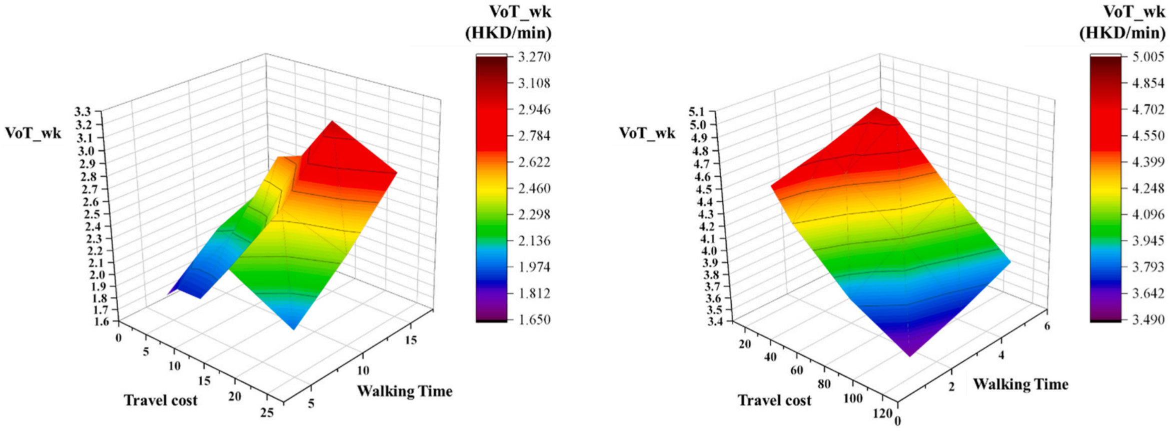


(a) VoT_w for Bus based on RRM (b) VoT_w for PLB based on RRM (c) VoT_w for Taxi based on RRM

Fig. 3. Values of waiting time at station based on RRM across different PT modes.



(a) VoT_wk for Bus based on RRM (b) VoT_wk for PLB based on RRM



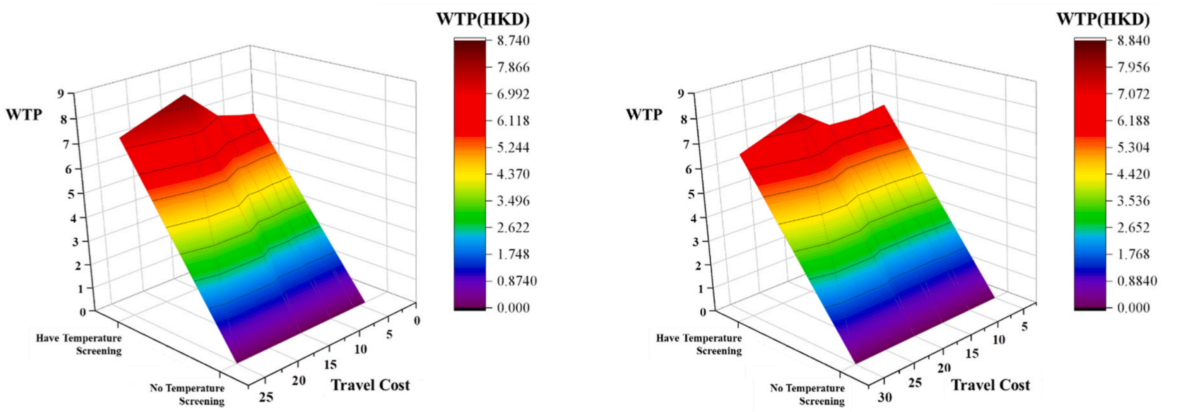
(c) VoT_wk for MTR based on RRM (d) VoT_wk for Taxi based on RRM

Fig. 4. Values of walking time based on RRM across different PT modes.

Consequently, if the chosen mode is fast but expensive, the traveler will only be willing to pay a smaller amount for a marginal reduction in travel time than if the chosen mode is slow but less costly.

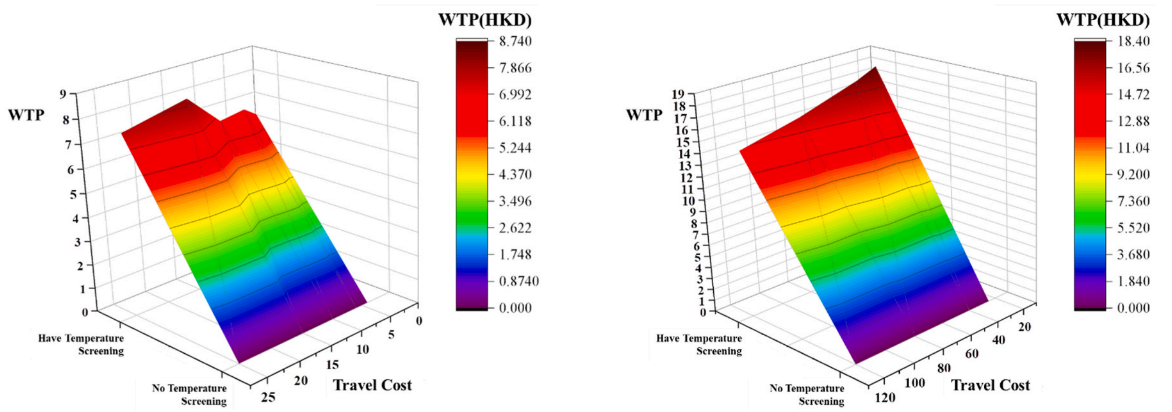
Fig. 3 illustrates the results of the value of waiting time (VoT_w) at bus/PLB stations and taxi stands. In accordance with Fig. 3, VoT_w at bus stations varies from 0.51 to 0.75 HK$/min (i.e., willing to pay approx. 5 to 7.5 HK$ in order to save 10 min of waiting time). VoT_w at PLB stations ranges from 0.78 to 2.67 HK$/min, which is relatively higher than the VoT_w at bus stations. Interestingly, Fig. 3(a) shows that VoT_w at bus stations increases from short to medium trips, and then decreases for longish trips. On the other hand, it appears that the VoT_w at PLB stations is higher for the medium trips, in order to further shorten their waiting time to less than 5 min. As for the taxi mode, passengers are willing to pay for 3.18 to 4.57 HK$/min to shorten the waiting time taxi stands, indicating a lower tolerance for the waiting time of taxi service (Lokhandwala and Cai, 2018). In particular, the VoT_w at taxi stands is higher when the taxi fare is low but the waiting time is long.

The trade-off between travel cost and walking time is depicted in Fig. 4. The value of walking time saved (VoT_wk) for bus mode varies from 1.81 to 3.09 $/min, while those for PLB and MTR modes vary from



(a) WTP for temperature screening on Bus

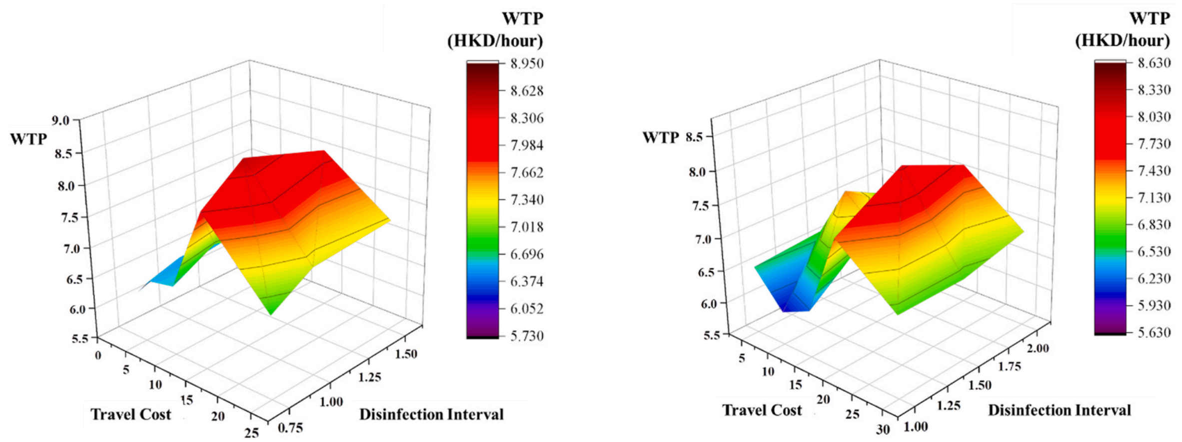
(b) WTP for temperature screening on PLB



(c) WTP for temperature screening on MTR

(d) WTP for temperature screening on Taxi

Fig. 5. Willingness to pay for temperature screening based on RRM across different PT modes.



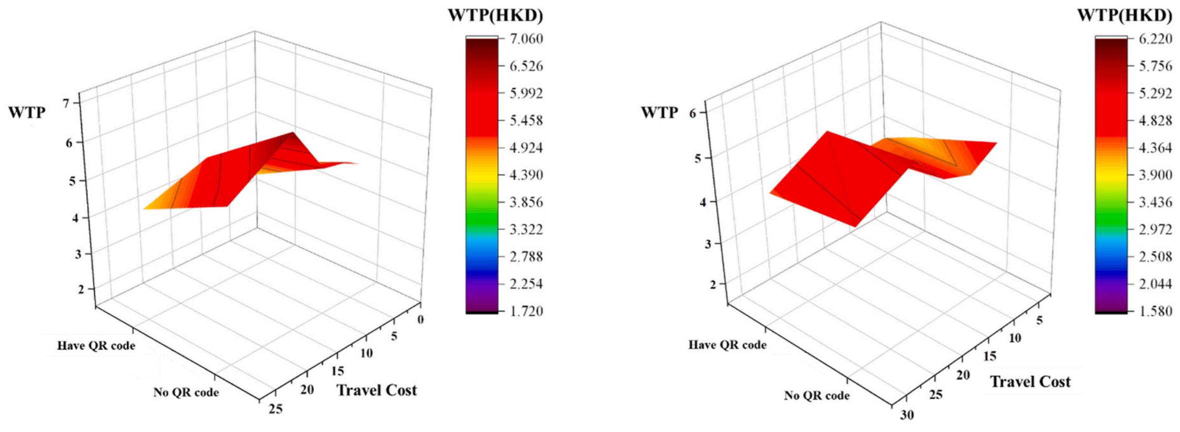
(a) WTP for disinfection on Bus

(b) WTP for disinfection on PLB

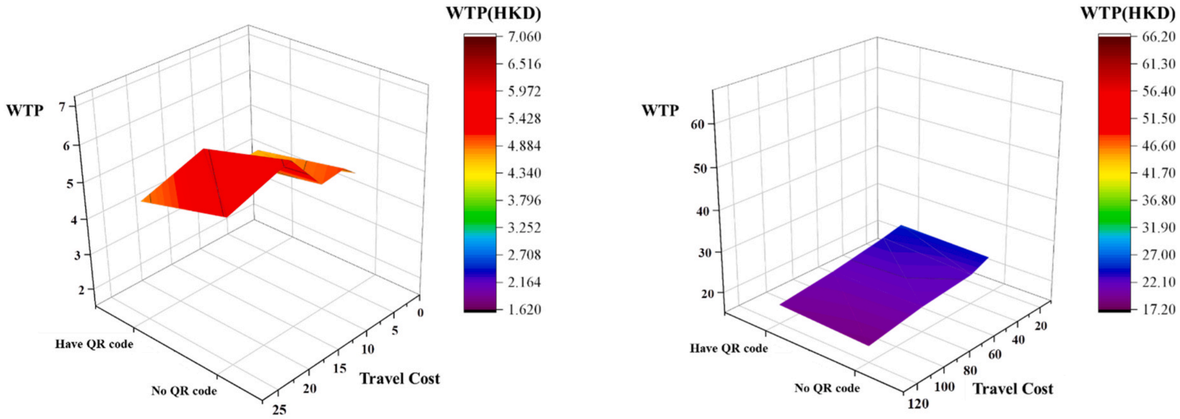
Fig. 6. Willingness to pay to shorten the disinfection interval based on RRM for bus and PLB modes.

1.61 to 2.77 $/min and 1.65 to 3.27 $/min, respectively (see Fig. 4 (a–c)). In addition, we also found a higher VoT_wk (ranging from 3.49 to 5.01 $/min) to shorten the total walking time from the trip origin to access a taxi mode, and from the alighting point of a taxi mode to the trip destination. Qian et al. (2017) revealed that a door-to-door taxi service is preferred by the users, while they show disutility for walking to and from the taxi pick-up and drop-off locations and have higher sensitivity to the convenience of taking taxis. Fig. 4(d) also demonstrates that taxi passengers who spend lower travel costs but more time walking are willing to pay more for reduced walking time, as compared with those who spend less time walking but higher travel costs.

Furthermore, we have calculated passengers' willingness to pay (WTP) for specific service features in the context of the COVID-19 pandemic. The estimation results in Fig. 5 suggest that individuals are willing to pay a maximum of HK$8.74 for passenger temperature screening on bus and MTR, and a maximum of HK$8.84 on PLB. On the other hand, they are willing to pay a maximum of HK$18.4 for such health service on taxis. In regards to the WTP estimates for vehicle



(a) WTP for QR code on Bus (b) WTP for QR code on PLB



(c) WTP for QR code on MTR (d) WTP for QR code on Taxi

Fig. 7. Willingness to pay for QR code based on RRM across different PT modes.

disinfection service improvement, Fig. 6(a) and (b) represents the WTPs to shorten the disinfection interval for bus and PLB (i.e., more frequent disinfection), respectively. Generally, the WTP for vehicle disinfection service improvement is lower for shorter trips (with lower travel costs) and then increases for medium trips before dropping again for longer trips. Such a result is intuitive, which can be explained from a psychological perspective. During a short trip, travelers may not consider it necessary to pay more for a more frequent disinfection; however, as the journey becomes longer, the need for such disinfection becomes more apparent. In spite of this, if the length of the travel trip exceeds a certain threshold, travelers may lose interest in improvements to the service, resulting in a decline in the WTP.

The trade-offs for the QR were estimated from the two perspective - (i) WTP for having a QR code for the travel, and (ii) WTP for the exemption of using a QR code for the travel. As discussed earlier, using a contact tracing QR code on PT_shared modes increases regrets among individuals with higher privacy concerns, as well as the regrets among those over age 65 regarding their choice of taxi mode. The WTP estimates for using/not using QR code across different modes are presented in Fig. 7. As shown in Fig. 7(a), our respondents are willing to pay HK$ 1.72 - HK$ 6.33 for having a QR code on bus, while the WTP for the exemption of using a QR code ranges from HK$ 4.78 - HK$ 7.06. As for the PLB mode, the WTP for having a QR code varies from HK$ 4.25 - HK$ 6.22, while a range of HK$ 1.58 - HK$ 3.76 was estimated for the exemption (see Fig. 7(b)). The range of the WTP for having a QR code for MTR travel is between HK$ 1.62 and HK$ 6.33, while the WTP for not using a QR code on MTR ranges from HK$ 2.82- HK$7.06 (see Fig. 7(c)). Finally, Fig. 7(d) demonstrates that individuals are willing to pay HK$ 17.2 - HK$ 44.1 for using a QR code on taxi, while that for the exemption can vary from HK$ 19.3 - HK$ 66.2.

The WTP estimates for both proactive and reactive health control measures seem higher on taxi, compared with other public transport modes. Such empirical results are overall consistent with some recent studies. For example, according to a nationwide survey in Spain during the pandemic, 40% of people responded that they would not be willing to pay more for using public transport if additional disinfection measures would be adopted (Awad-Núñez et al., 2021). The authors also revealed that individuals' willingness to pay for taxi/ride-hailing would be increased by certifying that only those not infected with COVID can use the service.

4.3. Policy simulation

A number of scenarios were chosen to evaluate the impacts of various health control policies on the choice probabilities of different transport modes. The estimation results of our RRM model are used for the simulation. With the focus on the context of traveling during the COVID-19 pandemic, here, we mainly discuss the influences of the proactive and reactive health control measures, and crowding levels of the vehicle.

A key objective is to explore whether implementing different health control measures on public transport during the pandemic will change public transport preferences. To begin with, the base cases in our policy scenarios is set as no temperature screening of passengers; disinfecting bus, PLB, MTR, and taxi per 1, 1.5, 0.75, and 1.5 h respectively; and providing contact tracing QR code only on taxis. Such a design was in accordance with the strategies implemented at the time when the survey

Table 5
Scenarios based on implementing different health control measures and changes in public transport modal preferences.

Policy Scenarios	Modal splits			
	Bus	PLB	MTR	Taxi
Proactive health control measures				
No passenger temperature screening (Base case)	14.00%	22.15%	32.37%	31.48%
Temperature screening for Bus passengers	**+3.52%**	−1.05%	−1.30%	−1.17%
Temperature screening for PLB passengers	−0.95%	**+4.24%**	−1.72%	−1.57%
Temperature screening for MTR passengers	−1.10%	−1.58%	**+4.99%**	−2.31%
Temperature screening for taxi passengers	−0.96%	−1.42%	−2.29%	**+4.67%**
Disinfection time interval (Base case)	14.33%	22.04%	32.12%	31.51%
Reduce the time interval of disinfection by 50% for Bus	**+1.05%**	−0.10%	−0.54%	−0.42%
Reduce the time interval of disinfection by 50% for PLB	−0.21%	**+2.29%**	−1.01%	−0.77%
Reduce the time interval of disinfection by 50% for MTR	−0.35%	−0.04%	**+0.66%**	−0.27%
Reduce the time interval of disinfection by 50% for Taxi	−0.45%	−0.18%	−0.57%	**+1.20%**
Reactive health control measures				
Provide a QR code only in Taxi (Base case)	13.02%	20.72%	29.90%	36.37%
Provide QR code in Taxi and buses, but no QR code for PLB and MTR	**+2.47%**	−0.69%	−0.86%	−0.92%
Provide QR code in Taxi and PLB, but no QR code for buses and MTR	−0.62%	**+3.04%**	−1.19%	−1.23%
Provide QR code in Taxi and MTR, but no QR code for buses and PLB	−0.71%	−1.10%	**+3.61%**	−1.80%
Provide QR code in all mode	+0.66%	+0.95%	+1.58%	**−3.19%**

was conducted. Table 5 presents the simulation results, and some insights are obtained.

Firstly, having a passenger temperature screening to identify potential virus carriers is appreciated by passengers and can increase the demand for each of the transport modes, with MTR seeing the biggest increase (i.e., +4.99%). Yet, in view of the large traffic volumes, installing temperature screening devices at MTR entry/exit gates is likely to be much more expensive compared with that for other modes. Secondly, reducing the time interval of disinfection by 50% (or, doubling the disinfection frequency) for the vehicle increases the probability of choosing that transport mode, with PLB ridership rising more significantly (i.e., +2.29%), followed by taxi (i.e., +1.20%). Unlike the clear instruction issued by franchised bus companies and metro operators, disinfection of taxis and PLBs is not regulated by organizations or large firms. To improve service quality, this calls for the collaboration between industry and the government to devise guidelines on cleaning and disinfection of PLB and taxi compartments. Furthermore, increasing the disinfection frequency of public buses and MTR trains would significantly increase labor and material costs, while the market shares of these two modes will only increase slightly. Thirdly, by looking through the scenarios of using the contact tracing mobile app on different transport modes for COVID contact tracing, it appears that the increase in PLB/MTR demand mainly comes from the demand loss of taxi. On the other hand, the increase in bus demand generally comes from the decrease in the demands of the three other modes by a similar percentage. When all modes provide a QR code to record a visit/ride, the demand for taxi will decline by 3.19%, while MTR demand is expected to increase by 1.58%. Our preliminary evaluation of the changes in public transport preferences suggests that health control measures are appreciated by passengers and promote public transport. Considering the large number of trips made, such effects are not trivial. In terms of percentage, however, these health control measures do not change the overall landscape.

Fig. 8 shows the changes in the mode choice probability with the crowding level of the public transport vehicles[3] for two trip purposes and three scenarios of in-vehicle travel time. In this case study, in-vehicle travel time of 10, 30, and 60 min were set as examples to represent short, medium, and longish trips.

Fig. 8(a–c) present the probability of selecting each PT mode for short, medium, and longish trips respectively for leisure purpose. In general, the probability of choosing MTR is the highest, followed by PLB and public bus. Seen from each scenario, as the crowding level increases, the choice probability of the MTR decreases, while the probability of using taxi service increases significantly. A remarkable decrease in the share of bus was also observed while the choice probability of PLB remains relatively stable. In Fig. 8(a–c), as the in-vehicle travel time increases, people are more sensitive to the crowding level of the vehicle, thus leading to a decline in the probability of choosing MTR (e.g., with a crowding level of 0.7, the probabilities of choosing MTR for short, medium, and longish trips are 0.44, 0.42, and 0.40, respectively). Interestingly, when the in-vehicle travel time increases from 10 to 60 min, the shift from using other modes to taxis reduces.

As for the business trips, Fig. 8 (d–f) show that when the crowding level exceeds 0.2 the probability of choosing taxi is the highest, followed by MTR. Compared with the three figures on the first row, we find that the choice probability of taxi in business trips is substantially higher than that in leisure trips. This is understandable because the high cost of taxi service is usually not a major concern for business trips. Similarly, the choice probability of the MTR decreases remarkably with the increase in crowding level, leading to the significant increase in the choice probability of taxi. For the short and medium trips, the shares of PLB and bus remain relatively stable, regardless of the crowding level. Nevertheless, for the longish business trip, the choice probability of PLB tends to be higher. This indicates that although the demand for taxi mostly shifts from MTR, PLB may serve as a substitute for taxis in longish trips. Overall, regardless of trip purpose, passengers seem to show greater tolerance to the crowding of PLBs, which could be attributed to its design of a maximum capacity of 19 passengers. Also, individual transport (i.e., taxi) or collective transport with lower passenger capacity (i.e., PLB) maybe preferred, as the exposure to public health risk can be reduced with contact with ‘strangers’ is minimized. Viegas (2008) proposed that taxis can play a more important role in bridging the gap between individual and collective transport in urban mobility. Nowadays, the rapid development of ride-hailing apps (e.g., Uber Taxi) makes “collective taxis” possible, which helps improve mobility and reduce congestion. As such, it is worth exploring passengers’ attitudes towards carpooling in the ‘new normal’ and their preference for collective taxis in a future extended study.

5. Conclusion and recommendations

To evaluate the effects of the proactive and reactive health control measures implemented for four public transport modes (i.e., public buses, public light buses, MTR, and taxi) on PT preferences, an online stated preference survey was conducted with 556 residents in Hong Kong during the COVID-19 pandemic. In particular, proactive measures include passenger temperature screening, disinfection, and air exchange rate of the compartment (to reflect good/poor ventilation), while the use of COVID tracing app (scanning a contact tracing QR code) belongs to the reactive measure. Trip characteristics including in-vehicle crowding level, fare, in-vehicle travel time, waiting time at station, walking time,

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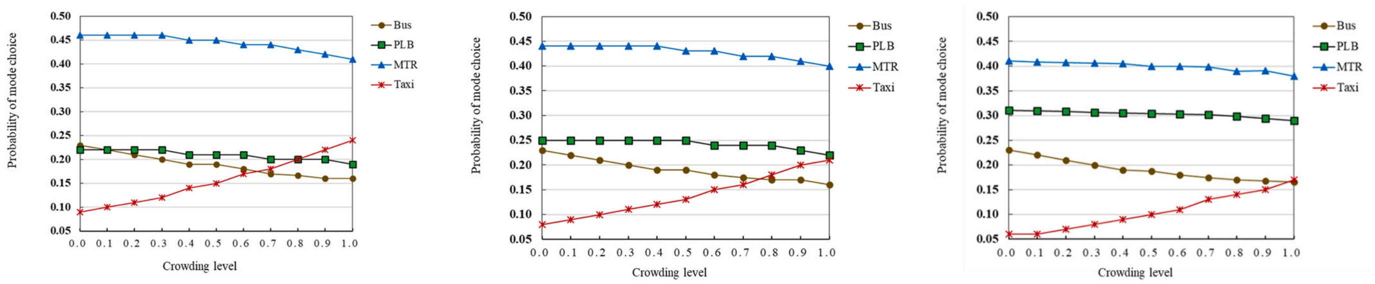
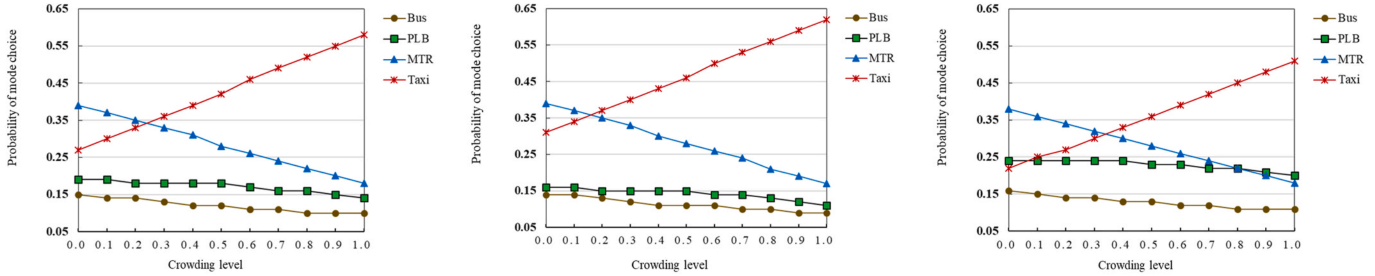
[3] Crowding levels were set for the public transport modes (including buses, PLBs, and MTR). Note taxis have no crowding issue, therefore the crowding level for taxi mode is set to be zero.



(a) Leisure trip (in-vehicle travel time = 10 min) (b) Leisure trip (in-vehicle travel time = 30 min) (c) Leisure trip (in-vehicle travel time = 60 min)



(e) Business trip (in-vehicle travel time = 30 min) (d) Business trip (in-vehicle travel time = 10 min) (f) Business trip (in-vehicle travel time = 60 min)

Fig. 8. Variations in PT mode choice probabilities with the crowding level.

and trip purpose were also examined. In public transport-oriented cities like Hong Kong, a substantial modal shift from public transport to private mode may not be feasible, especially in those with very low rates of private car ownership. Our research analyzes the modal shifts within various modes of public transport when health control measures are implemented. Such an investigation is important for formulating sustainable 'new normal' for public transport.

This study utilized a RRM model aiming to capture individual's regret aversion psychology in the context of the COVID-19 health crisis. As the fear and uncertainty about infection risk arise, regret aversion psychology may drive the decision-making of travel mode choice. The results from the RP-RRM model (the regret-based panel mixed multinomial logit model) revealed that, traveling by PT_shared modes (including MTR, bus, and PLB) are intrinsically preferable to traveling by taxi, while such preference would be reduced significantly for business trip.

In general, having passenger temperature screening, the use of COVID tracing app, and more frequent disinfection of bus and PLB, contribute to a decrease in potential regrets to the chosen mode. Nonetheless, travelers with higher privacy concerns are averse to the use of QR code on PT_shared modes, while the elderly (aged 65+) also have increased regret for taxi mode due to the use of QR code. Interestingly, although respondents seem to be unaware of the in-vehicle air quality (i.e., variable of in-vehicle air exchange rate, AER), increased AER appears to cause a marginal extra decrease in potential regret to MTR mode for those with relatively high health concerns. On the other hand, passengers generally show greater regrets for the chosen mode due to the overcrowding of the vehicle, increased travel cost and in-vehicle travel time, longer walking time, and longer waiting time at stations. Aside from that, these passengers are more sensitive to the service quality (e.g., waiting time at public bus/PLB stations, crowding level of the MTR train car) when it comes to business trips.

The policy simulations provide additional intuitive information for policy makers. For example, pre-boarding passenger temperature screening to identify potential virus carriers would contribute to an increase in the demand for each transport mode, with MTR seeing the largest increase. In addition, doubling the frequency of vehicle disinfection would be more effective for promoting the use of PLB. Moreover, if all public transport modes provide a contact tracing QR code on board, the demand for taxi will slightly decrease while the demand for public bus, PLB, and MTR would slightly increase.

Variations in PT modal preference with the crowding level of the public transport are significant across different scenarios of trip purposes (i.e., leisure and business) and in-vehicle travel time (i.e., short, medium, and longish trips). For leisure trips, the demand for MTR continues to be the highest among all modes. Nevertheless, as the crowding level increases, MTR and bus shares gradually decrease, resulting in an increase in taxi demand. For the business trips, the probability of choosing a taxi mode becomes higher than that for the MTR when the in-vehicle crowding level increases. The demand for taxi mainly shifts from MTR, while in longish trips PLB could be a substitute for taxis.

Overall, the results convey a mixed message to policy makers. On the one hand, health control measures are indeed appreciated by passengers and promote public transport use in general. Such effects are not trivial considering the extremely large travel volumes. On the other hand, in terms of percentage health control, measures do not radically change the landscape of public transport. Therefore, they should be selectively used. For example, efficient temperature screening systems (e.g., non-contact infrared thermal imagers for mass fever screening) may be considered for the MTR and bus services, whereas a contact tracing app is probably not an ideal solution for those travel modes due to the large traffic volume and privacy concerns. Our analysis and simulations further suggest increasing service frequency may be a promising measure in promoting public transport use in the presence of health risks. This is because crowding and waiting time have significant effects on passengers' PT preferences, while also influence virus transmission risk (i.e., higher transmission risk under higher crowding level and longer waiting time at stations and bus stands). Increasing service frequency will address these issues simultaneously: increased frequency reduces waiting time (and thus total travel time). As a result, the service quality of public transport increases while the risk of infection is reduced. More importantly, increased frequency and capacity would reduce crowding and thereby the infection risk. All these positive effects would attract more passengers to public transport, and the resultant high-capacity utilization (load factor) will moderate the cost increase associated with higher service frequency. Of course, much of the associated benefits may be achieved by adding more cars to MTR services.

A formal cost-benefit analysis on this promising solution may be considered. Although our findings and conclusions are drawn from updated data and analysis, it should be noted that the focus of this paper is on the potential modal shift among the public transport modes in a background of public transport-orientated city. A larger sample would be beneficial for a more in-depth investigation, as well as the consideration of other trip characteristics and pandemic control measures. This study is limited to the consideration of disinfection, air exchange rate of the vehicle, and contact tracing applications that could become a permanent feature for public transport as health control measures. Mask wearing is not included in the current study (in part because there is a view that it is unlikely to become a permanent compulsory feature). The role of mask wearing policy that might play on the mode choice of multiple public transport services should be examined in extended studies. In addition, since Hong Kong had relatively good pandemic control until the beginning of 2022, passengers' preference may change in the case of serious pandemic conditions, or when pandemic is of minimum concerns. Furthermore, examining a variety of trip purposes in one study may introduce additional effects related to a specific origin-destination route. Since it is important to collect more information about the status quo alternative, it would be worthwhile to examine the mode choices for commuting trips in the extended studies using pivot design. Specifically, respondents' current job status, workplace location, built environment, current commuting mode, travel distance, travel time and fee, etc., will be inserted by each respondent to create individualized choice sets. The current research focuses on the comparison between leisure trips and business trips. In future studies, the effects of crowding in metro/train could be further investigated by incorporating the SP design with a detailed description of the occupancy rates relative to the standing and seated capacities of a train car. For example, previous studies used seat occupancy rate, number of passengers standing per m^2, and standing time to get seated, etc. as indicators of crowding in train (see Hensher et al. (2011), Li and Hensher (2011), Tirachini et al. (2013), Yap et al. (2020), and Singh et al. (2023)). And lastly, it will be worthwhile to include other alternatives such as walking, cycling, or other PM (personal mobility) modes, which are expected to have remarkable increases in the market share in the post-pandemic world.

While research on the impact of COVID-19 is fast moving, to the best of the authors' knowledge, this study is the first (i) to focus on a public transit-oriented city; (ii) to apply regret theory in PT mode choices, and (iii) to analyze the detailed PT preferences in a 'new normal' context, where COVID infection still exists, but mobility restrictions are lifted. This study is one of the many efforts aiming for the good design of the 'new normal', and to assess the effectiveness of strategies for promoting public transport use. In future studies, it will be worthwhile to explore transit users' preferences in integrated multi-modal transport networks with various health control measures. As such, we can better understand the trade-offs between unimodal and multi-modal travels, thus planning for a more sustainable transit-oriented multi-modal transportation systems in the post pandemic world (Wang et al., 2022). Besides, the multi-modal public transport alternatives should be described by additional attributes related to the transfer phase (Arentze and Molin, 2013; Nielsen et al., 2021), as well as the difference in health control measures between public transport modes. By leveraging the current study, it will also be possible to develop a route recommendation system tuned towards pandemic fear levels for public transportation (see, for example, Sun and Wandelt, 2021), as fear levels may dominate decision making process compared to other service attributes.

Author statement

All authors in this study have contributed significantly. Specifically, each author's main contribution is listed as follows, which doesn't fully summarize precisely the overall contribution. Tiantian Chen: Main contribution: Conceptualization, Methodology, Validation, Resources, Data Curation, Writing - Original Draft, Writing - Review & Editing Xiaowen Fu: Conceptualization, Methodology, Validation, Resources, Writing - Original Draft, Writing - Review & Editing, Project administration. David A. Hensher: Main contribution: Conceptualization, Methodology, Validation, Resources, Writing - Original Draft, Writing - Review & Editing. Zhi-Chun Li: Main contribution: Conceptualization, Methodology, Validation, Resources, Writing - Original Draft, Writing - Review & Editing. N.N. Sze: Main contribution: Conceptualization, Methodology, Validation, Resources, Writing - Original Draft, Writing - Review & Editing.

Data availability

Data will be made available on request.

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