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Data-driven analysis and modeling of individual longitudinal behavior response to fare incentives in public transport

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Abstract

Incentive-based public transport demand management (PTDM) can effectively mitigate overcrowding issues in crowded urban rail systems. Analyzing passengers' behavioral responses to the incentive can guide the design, implementation, and update of PTDM strategies. Though several studies reported passengers' responses to fare incentives, they focused on passengers' short-term behavioral responses. Limited studies explore passengers' longitudinal behavioral responses for different types of adopters, which is important for policy assessment and adjustment. This paper explores and models passengers' longitudinal behavior response to a pre-peak fare discount incentive using 18 months of smart-card data in public transport in Hong Kong. We classified adopters into six types based on their temporal travel pattern changes before and after the promotion. The longitudinal analysis reveals that among all adopters, 19% of users change their departure times to take advantage of fare discounts but do not contribute to the goal of reducing peak-hour travel. However, these adopters are more likely to sustain their changed behavior in a long term which is not desired by the incentive program. The spatial analysis shows that the origin station distribution of late adopters is relatively more diverse than the early adopters with more trips starting from distant areas. The diffusion modeling shows that the majority adopters are innovators and the word-of-mouth diffusion effect (imitators) is marginal. The discrete choice model results highlight the heterogeneous impact of factors on different types of adopters and their values of time changes. The significant factors common to adopters are: departure time flexibility, the expected money savings, the required departure time changes, and work locations. The findings are useful for public transport planners and policymakers for informed incentive design and management.

Keywords Smart card data · Longitudinal analysis · Fare discounts · Behavioral responses · Adoption patterns · And discrete choice modeling

Leizhen Wang and Xin Chen are co-first authors.

Extended author information available on the last page of the article

Introduction

The rapid progress of urbanization leads to increasing congestion in public transport systems in cities. By far, many cities' metro systems are struggling given the outpacing demand for travel (Wang et al. 2018). The intuitive way to relieve the overload issue is adding physical capacity by extending the network or updating operation infrastructures, which is, however, impractical considering the massive time and financial cost. Public transport demand management (PTDM), i.e. designing policies to maximize the usage of the existing capacity, is a promising and sustainable solution to address crowding in metro systems.

Traffic demand management (TDM) strategies in car traffic (e.g., shifting modes and congestion pricing, etc.) have been widely studied and successfully implemented in cities, such as Stockholm, Singapore, and London (Gärling and Schuitema 2007; Tillema et al. 2013). However, TDM strategies cannot be directly transferred to PTDM because public transport passengers tend to have less flexibility in routes or departure times compared to car drivers (Halvorsen et al., 2020). Different from the TDM strategies, the goal of PTDM is to redistribute the travel demand in time and space rather than using other modes. Several cities have implemented or trialed PTDM strategies to manage peak travel, mostly in the form of incentives encouraging off-peak travels, such as 'Free Before 7' in Melbourne, 'Travel Smart Program' in Singapore, and the 'PERKS Reward' in San Francisco (Ma and Koutsopoulos 2019). The key technology enabler for these programs is the smartcard system facilitating the trip distance-based fare charging. The empirical evaluations show that generally, 3–10% of peak demand switches to off-peak travels (Currie 2009; Greene-Roesel et al. 2018; Halvorsen et al. 2016). However, Ma and Koutsopoulos (2019) found that the PTDM program efficiency is relatively low given that many passengers may benefit from incentives without contributing to the system crowding reduction, e.g., already traveling in the incentive promotion period or using paths not passing through critical links. Other PTDM strategies are also reported in addressing metro crowding, such as encouraging employers to allow flexible work schedules and providing real-time crowding information on platforms (Pefitsi et al. 2021; Yang and Long Lim 2018). In a recent review, Ma et al. (2021) synthesize the demand management strategies in public transport and discuss incentive-based ideas leveraging new technologies and computing techniques.

Understanding passengers' behavioral responses to PTDM strategies is essential for informed incentive design and management. Some studies used surveys to understand passengers' behavioral response to promotions. For example, Zhang et al. (2014) conducted a stated preference (SP) survey in the Beijing metro and reported that the promotion-based PTDM is effective in managing peak demand and the flexible work schedule is critical for passenger adoption. Wang et al. (2018) conducted an SP survey in the Beijing metro to study the effects of different incentive mechanisms and reported that price adjustment is the most efficient tool to influence passengers' responses. Azhdar and Nazemi (2020) evaluated Tehran metro passengers' stated preferences over different types of incentives and found that discounted tickets, more seats, and free Wi-Fi and breakfast discount coupons are influential in altering passengers' response to promotion policy. The SP-based analysis provides useful insights into passengers' behavioral responses in hypothetical scenarios. However, it may lead to biased conclusions due to the lack of realism and behavioral incongruence (Dixit et al. 2017; Wang et al. 2020). In addition, the SP survey is usually conducted once or several times, thus providing limited information about longitudinal behaviors (evolutions of behavior).

The availability of automated fare collection (AFC) data is the enabler for a broad scope of behavioral studies in public transport. It drives the detailed analysis of mobility patterns and choices and the customer-oriented performance evaluation and monitoring (Mo et al. 2022; Nassir et al. 2019, 2017). AFC data facilitates not only the analysis of the aggregate characteristics of when, where, and how passengers travel in the system but also the disaggregated analysis of the mobility patterns of groups and/or individuals (Koutsopoulos et al. 2019). Several studies studied passenger behavioral responses to incentive-based PTDM strategies using AFC data. For example, Halvorsen et al. (2016) evaluated the response to an off-peak discount promotion in Hong Kong (offering a 25% discount for passengers completing their trips before the morning peak) and evaluated its effectiveness. Using AFC data from before and after the implementation of the promotion, they analyzed the impacts at the system and group levels. The results demonstrated that different passenger groups had different responses to the promotion. Halvorsen et al. (2020) further performed an individual-level analysis using a logit model. They concluded that the amount of time passengers had to shift to take advantage of the promotion, fare savings, work flexibility, and price sensitivity were major factors in changing their behavior. Using the same data in Hong Kong, Anupriya et al. (2020) found that the 25% discount promotion resulted in a statistically significant but very small reduction in regular commuters' average arrival times using the difference-in-difference method. They concluded that fares and crowding were major factors in changing commuters' behavior. Wang et al. (2020) evaluated different classes of passengers' behavior responses to discount policy using smart card data from 20 working days in Beijing. They concluded that all classes of passengers' behavioral responses were affected, but to varying degrees, by fare savings, the required change in departure time, and travel frequency.

However, the above studies focused on the short-term response to a promotion (i.e., 1–3 months after the promotion), and few studies reported on the long-term behavior. Understanding the long-term sustainability of the behavioral change, originally induced by the promotion, is important as the attrition of responsive passengers can be significant (Halvorsen et al. 2020). For example, Ma et al. (2020) developed a cluster-based approach to analyze passengers' short-term and long-term behavior in response to promotion using AFC data and used an optimization model to assess its impact on the fare incentive design in Hong Kong. They identified adopters who changed their departure times in the first two months after the promotion was implemented (early adopter) and track the behavior of these adopters for a following two-year period (short and long terms response). They found that users who have high flexibility in schedule and familiarity with the system and travel relatively long distances are more likely to shift their travel times in the short term. However, 35–40% of passengers who initially adopted the promotion will eventually revert to their previous travel time periods in the long-term. They argued that the promotion designs should be adjusted/renewed over time to sustain the initial response given the attrition of early adopters.

The above study provides a good reference on longitudinal behavior analysis framework and methodology using AFC data. However, it focuses on the longitudinal behavioral response of early adopters in an aggregated group level. It lacks a comprehensive analysis of all types of adopters, such as late adopters (e.g., adopt promotion 3 months after) or adopters changing access/egress stations. It also lacks of choice modelling to better understand important factors contributing to the heterogeneous longitudinal behavioral response at an individual level. The study addresses these gaps by defining and proposing a data-driven approach to infer different types of adopters in response to incentive based PTDM strategy, and developing discrete choice models to model their heterogeneous behavior

response as a function of mobility patterns (proxies of sociodemographic information) and incentive attributes extracted from AFC data. It aims to address the following questions:

- How do individuals respond to a promotion in time and space?
- How do these responses to a promotion change over time for different types of adopters?
- What are important factors impacting these heterogeneous behaviors and how?

Answering above questions provides useful insights into the longitudinal behavior of individual passengers in response to incentive based promotion, and guides the design, implementation and update of PTDM strategies. For example, efficient promotion schemes could be designed to reward individuals whose behavior changes contribute to systems and are sustainable; or providing dynamic, personalized incentives targeting both who and when intriguing continuous interests. The paper makes the following contributions:

- Proposing a robust data-driven approach in identifying different types of adopters in response to fare incentive using AFC data in public transport
- Analyzing the longitudinal incentive adoption and attrition behavior of individuals, and exploring the incentive diffusion process in the studied public transport population
- Modeling individual behavioral response to incentives for different types of adopters and identifying important factors impacting their choices

The remaining paper is organized as follows: The Methodology section introduces the research framework and develops a data-driven approach to automatically identify adopters and their adoption dates in response to incentives. The case study uses 18 months of AFC data in Hong Kong and presents the mobility patterns and longitudinal behavior responses of different types of adopters. It also models the incentive diffusion process and individual adoption behaviors in the studied population. The final section summarizes the main conclusions and discusses future research directions.

The incentive program and data

The incentive program is the ‘early-bird’ promotion launched in September 2014 by Mass Transit Railway (MTR), Hong Kong. MTR is a major subway system serving urban areas of the New Territories, Kowloon, and Hong Kong Island. The system has 11 rail lines covering 218.2 km in length with 159 stations. The average number of trip transactions is 5 million per day and almost all transactions are paid with Hong Kong’s Octopus Card. The Octopus card is a stored value system in which a deduction is made for every trip based on the travel distance and no fare cap for the adult card users in the promotion (Halvorsen 2015).

The incentive program is a pre-peak fare discount program based on passenger exit stations and times using the MTR subway system. Figure 1 shows the geographical network of the MTR system and targeted stations for the promotion. It offers 25% fare discount to adult-card passengers exiting the designated 29 stations (the dash rectangle area) between 7:15–8:15 am (the pre-peak). It aims to mitigate the congestion on critical links of the urban rail system in the morning peak (8:15–9:15 am). The trip

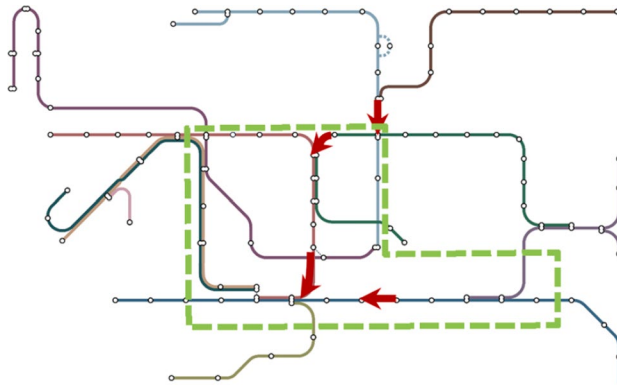


Fig. 1 Network, critical links (red arrows), and eligible promotion stations (dashed area) (adopted from Ma et al. (2020))

fare ranges between 5–50 HKD (≈ 0.65 – 6.5 USD), with a 25% discount equivalent to 1.25–12.5 HKD (≈ 0.16 – 1.6 USD) per trip. Detailed description of the program can refer to (Halvorsen et al. 2020).

The Octopus card transaction data is used for the study. It records the trip transaction information, including the anonymized card ID, tap-in/tap-out times, tap-in/tap-out stations, card type, and the fare deduction. For example, a trip transaction record is a passenger with a card ID 90012xxxx entered station 48 at 15:16 and exited from station 52 at 15:27 on July 7, 2014 and the trip cost is 5 HK dollars. Note that the anonymized ID is unique for an individual passenger across days, which facilitates the tracking of individuals' behavior changes before and after the implementation of the promotion program.

The panel data is constructed for our analysis. Considering the program launched in September 2014, AFC trip records data from July 2014 to December 2015 are used for the before and after analysis. Existing study shows that frequent passengers are dominant in the promotion (Ma et al. 2020), and a better understanding of their response can provide useful insights for promotion design. We use the following criteria to select panel passengers for the longitudinal analysis: (a) passengers have more than 10 trips per month using any promotion stations in the weekday morning period (i.e., exit between 6:15 am and 10:00 am) between July 2014 and August 2014, (b) passengers whose card type is adult, and (c) passengers who have trip records for any three consecutive months between July 2014 and December 2015.

An initial sample of 2.07 million passengers who have trip records from 2014 to 2015 was sampled. 22,628 passengers were selected for the panel analysis, accounting for approximately 1.1% of the studied public transport population. After preprocessing the AFC trip data (e.g., invalid or incomplete trips), 18 million trip records were extracted (an average of 1.5 trips per day per passenger).

Figure 2 shows distributions of trip travel times and departure times for the panel data and the population of adult commuters targeted by the promotion program on typical weekdays. The results show that the panel data can reasonably represent the targeted adult commuter population in terms of travel patterns.

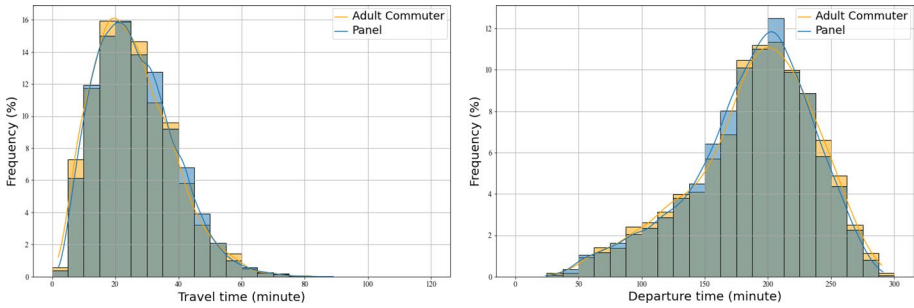


Fig. 2 Distributions of trip travel times (left) and departure times (right) for the panel and population data. Note that the departure time in the right figure is the time difference from 5:00 am, e.g., the departure time of 60 min means 6:00 am

Methodology

Figure 3 describes the proposed research framework for the longitudinal behavior analysis driven by AFC data, including adopter identification (adoption and adoption times, attrition and attrition times), aggregated analysis (longitudinal, spatiotemporal patterns and incentive diffusion process), and disaggregated analysis (adoption choice modeling for different types of adopters). All analysis or models are driven by AFC data and crawled network data.

- **Adopter identification.** It constructs the panel for the longitudinal behavior response analysis and identifies passengers’ adoption and attrition behavior towards promotion using AFC data. It develops a change point detection method to automatically identify incentive adopters and their adoption and attrition times, facilitating the longitudinal analysis.
- **Aggregated analysis.** It systematically analyzes adopters’ longitudinal behavior response toward the incentive program over a long-time span in both time and space dimensions. It includes different types of adopters and their statistics and spatiotemporal patterns (distributions of departure time changes, money savings, and origin/desti-

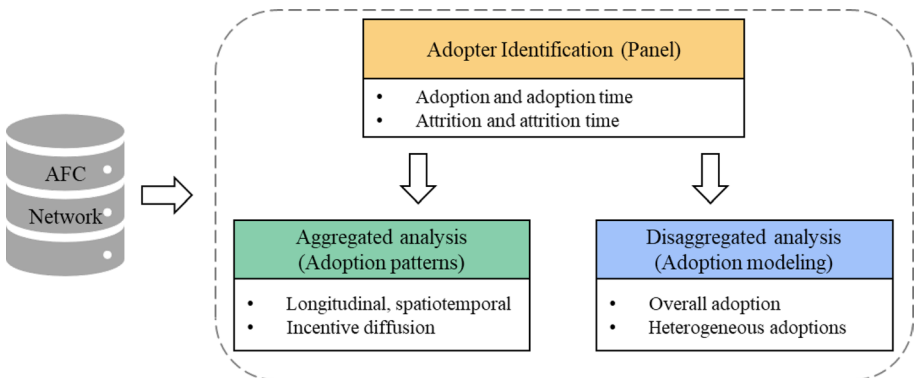


Fig. 3 Research framework of the longitudinal behavior analysis of incentives

nation stations). It also models the incentive diffusion dynamics in the studied public transport population.

- Disaggregated analysis. It develops a discrete choice model to study the overall behavior response to the fare incentive. Also, it builds a set of discrete choice models to study the heterogeneous behavior response of different types of adopters, including early/late, attrition/sustained, and early morning/late morning adopters.

Adopter identification

The adopter identification identifies who adopt the incentive (i.e., change their travel behavior) and when they adopt and drop it over the time after the promotion. Formally, the adopters are defined as passengers who change their behavior (e.g., exit time or station) in order to take advantage of the incentives (e.g., fare discount). Specifically, for the studied pre-peak fare discount incentive program (awarded exiting designated stations at the pre-peak period), the adopters are those passengers who regularly travel outside of the incentive time period (and/or stations) before the promotion was conducted, and then significantly increase the proportion of trips within the incentive time period (and/or stations) after the promotion.

The adopter identification includes two sub-tasks, namely behavior change detection and the association of the change to the studied event (i.e., incentive program). Traditionally, the behavior change detection studies used the rule-based approach based on monthly travel patterns. For example, Ma et al. (2020) define $\theta_{i,t}^m$ be the fraction of the number of trips within a time period t (e.g., 7:15–8:15 am) over the total number of morning trips (e.g., 6:15–9:15 am) in month m for individual i . A time period t is identified as the regular travel period of an individual i in month m if $\theta_{i,t}^m > \alpha$, where α is a pre-determined threshold. $\alpha = 0.5$, for example, indicates that a time period t is considered as an individual’s regular travel period if more than 50% of his/her morning trips in month m are during that time period. Let m' be the month when a promotion starts and t' the promotion time period. An adopter is identified as:

$$\text{Passenger } i \text{ is } \begin{cases} \text{adopter} & \text{if } \theta_{i,t'}^{m'-1} < \alpha \text{ and } \theta_{i,t'}^{m'+1} \geq \alpha \text{ (a)} \\ & \text{and } \Delta\theta_i = \theta_{i,t'}^{m'+1} - \theta_{i,t'}^{m'-1} \geq \beta \text{ (b)} \\ \text{nonadopter} & \text{otherwise} \end{cases} \quad (1)$$

Adopters are those users who change their regular travel times (Eq. 1a) before and after the promotion and these changes are significant (no less than a pre-defined threshold β , e.g., $\beta=0.10$). The fraction of the number of trips in the target period in Eq. 1a could be estimated using several months (rather than a single month). Equation 1b addresses random fluctuations of travels across days in identifying adopters.

However, such a method uses monthly travel patterns as the analysis unit and it cannot identify passengers’ exact adoption and attrition dates. In addition, passengers might vary departure times by day, dependent on for example home responsibilities and work commitments. It may detect invalid or biased behavior changes given its sensitivity to the pre-determined threshold and the unreliable trip ratio calculations. For example, suppose a passenger is identified as not traveling in the promotion period before the promotion, and she/he travels just once in a month after the promotion and this trip is within the promotion time period. Then, this passenger would be inappropriately identified as an adopter.

To address the above issues, we develop a time-series change point detection method to identify adopters and their corresponding adoption dates based on daily travel records. In the model, the passenger’s daily exit time is modeled as a random process $E = \{e_0, \dots, e_t, \dots, e_{T-1}\}$, where e_t is the passenger’s exit time of the first morning trip on day t (e.g., 7:22 am), and T is the total number of days in the study. The passenger exit time process is assumed to be piecewise stationery (e.g., K segments) which results in a set of time points $t_1 < \dots < t_k < \dots < t_K$ when significant changes may happen. These change points are identified by minimizing the difference between the exit time of the change point and the mean exit time of that segment:

$$\operatorname{argmin}_{t_1, \dots, t_k, \dots, t_K} \sum_{k=0}^K \sum_{t=t_k}^{t_{k+1}-1} \|e_t - \bar{e}_{t_k, \dots, t_{k+1}}\|^2 \tag{2}$$

where $\bar{e}_{t_k, \dots, t_{k+1}}$ is the empirical mean of the segment $e_{t_k}, e_{t_k+1}, \dots, e_{t_{k+1}-1}$.

The identified change point t_k using Eq. 2 is the time when passengers change their routine travels. For the example in Fig. 5e in section "Longitudinal, spatiotemporal adoption pattern", the passenger changes his/her regular travel from 6:55 am to 7:16 am, and its identified change point is October 14, 2014 because of its mean exit time significantly change after that day. The theoretical discussion of the change point detection method is provided in Truong et al. (2020).

The behavior change detection task gives a set of candidate dates when an individual may adopt and drop the incentive. To associate the behavior change dates to the incentive, we develop a rule-based association approach based on the before-and-after analysis. Let R_i^k be the proportion of trips within the promotion period (e.g., departure time is between 7:15–8:15) over the next j trips after t_k (e.g., the next 20 trips after September 15) for individual i . Similarly, let R_i^b be the proportion of trips within the promotion over a certain time (e.g., two months) for individual i before the promotion is launched. An adopter is identified as:

$$\text{Passenger } i \text{ is } \begin{cases} \text{adopter} & \text{if } R_i^k - R_i^b \geq \beta \\ \text{nonadopter} & \text{otherwise} \end{cases} \tag{3}$$

Equation 3 indicates that the adopters are those who significantly increase their travels in the promotion period compared to the base travels before the promotion program is launched. We infer the adoption date of individual i as the first change point t_k that satisfies Eq. 3.

To further improve the association reliability, we conduct post refinement processes for initial adopters identified in Eq. 3 by excluding those whose travel pattern changes are caused by seasonal factors. Specifically, we identify if an individual has seasonal travel pattern changes by comparing his/her travel patterns of the same month for different years. The individuals identified as having seasonal travel changes will be excluded from the initial adopter set. Also, we exclude individuals whose used stations (origin or destination or both) changed after the promotion compared to those before the promotion. This would avoid the risk of accounting for the life or work changes in the identified adopter set. Note that the same approach in Eq. 3 is used to identify the adopter’s attrition date.

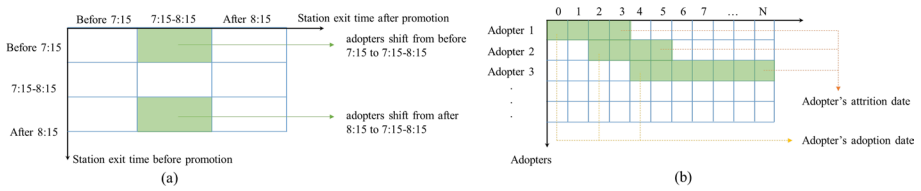


Fig. 4 Cross-tabulation for behavioral analysis: the percentage of adopters' type

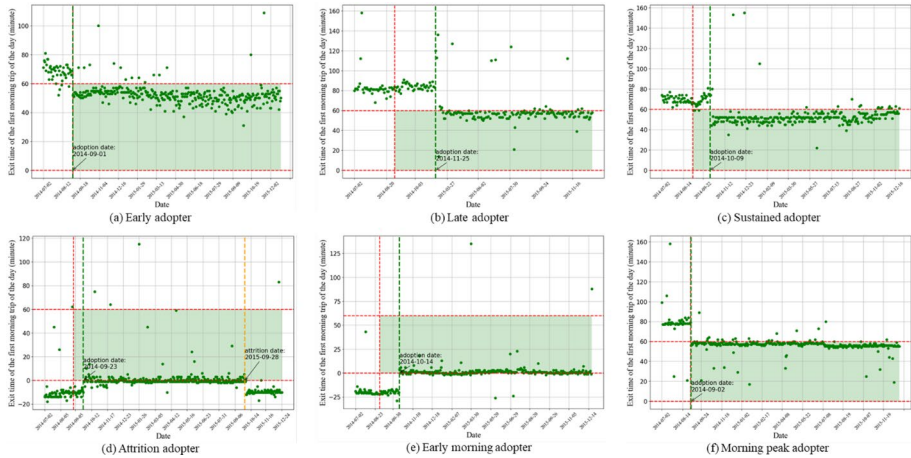


Fig. 5 Adopter types and the corresponding travel patterns (note that the vertical axis shows the difference between the trip's exit time and 7:15 am in minutes. For example, 0 represents 7:15 am, 60 represents 8:15 am, and -15 represents 7:00 am)

Aggregated analysis

Longitudinal, spatiotemporal adoption pattern

We analyze adopters' temporal behavior changes using a cross-tabulation table as shown in Fig. 4. The exit time of the morning peak travel of adopters is divided into three categories: before 7:15, 7:15–8:15 and after 8:15. The vertical and horizontal axis of Fig. 4a represent the exit time category of the morning peak travel of adopters before and after promotion, respectively. The difference between the exit time category before and after promotion divides the adopters into different types. Figure 4b shows adopters' long-term behavior changes after the implementation of the promotion policy. The green cells in each row show the adopter's adoption and the empty cells attrition behavior over time. Based on these, different types of adopters and their corresponding statistics could be calculated.

Figure 5 shows the different groups of adopters categorized using different mobility attributes, including adoption date, behavior change sustainability, and departure times before the promotion. The corresponding definitions are:

- Early adopter (Fig. 5a): Passengers who adopt the promotion in the first two months after the promotion is implemented.

- Late adopter (Fig. 5b): Passengers who adopt the promotion policy two months after the promotion.
- Sustained adopter (Fig. 5c): Passengers who adopt the promotion at a certain time and sustained afterward until December 2015.
- Attrition adopter (Fig. 5d): Passengers who adopt the promotion at a certain time and then drop it (attrition) afterward.
- Early morning adopter (Fig. 5e): Passengers who switch from the early morning (6:15–7:15 am) to the off-peak period (7:15–8:15 am) to get the discount.
- Morning peak adopter (Fig. 5f): Passengers who switch from peak period (8:15–9:15 am) to an off-peak period (7:15–8:15 am) to get a discount.

Note that we simply define different types of adopters to be pair-wised rather than exclusive among types. That is the early and late adopters are paired groups and the percentages of adopters in that paired groups are summed up to 100% (similar to sustained/attrition adopters, and early morning/morning peak adopters). This categorization is more relevant and meaningful for practical understanding and deriving behavior insights from the pattern and modeling analysis.

In addition, the departure time change and expected money savings are key factors influencing passengers' behavioral responses to the incentive (Halvorsen et al. 2020; Wang et al. 2020). To understand these for different types of adopters, we define the departure time change of an individual as the time difference (in minutes) between the average departure times of the individual after and before the promotion. We define the expected money savings as the average ticket fare times the discount levels. We also visualize the spatial distribution of adopters at origin and destination stations to analyze the spatial equality of the incentive.

Incentive diffusion process

Understanding the incentive diffusion process over time is important for program marketing and adoption forecasts. The traditional choice modeling cannot capture the diffusion process of network interventions, such as adopters with policy interventions. Many diffusion models are proposed in the marketing science domain and widely applied in other application areas, such as new technology (El Zarwi et al. 2017), agriculture (Sunding and Zilberman 2001), automobile industry (Dargay and Gatley 1999), and many other industries (Delre et al. 2007; Desiraju et al. 2004; Schramm et al. 2010).

Conceptually, the introduction of incentive policy in public transport is similar to that of new technologies or products in the market. We treat the incentive policy as a new product and the number of passengers who adopt it as buyers and explore the incentive diffusion process by fitting diffusion models, such as the Bass model (Bass 1969). The Bass model categorizes adopters into two distinct groups, i.e. innovators and imitators. Innovators are individuals who decide to adopt the promotion independently in a social system, and imitators are adopters that are influenced in the timing of adoption by the pressures of the social system (Bass 1969). The probability $P(t)$ of a non-adopter will adopt at time t is:

$$P(t) = p + \frac{q}{m} Y(t) \quad (4)$$

where p , q are coefficients of innovation and imitation in the diffusion process, m is the total potential market for the promotion policy and $Y(t)$ is the number of adopters before time t . Physically, p reflects the importance of innovators in the system, and q reflects the

influence of previous adopters on imitators or word-of-mouth effect. In practice, the $P(t)$ and $Y(t)$ are observed and used to calibrate p , q , and m .

Figure 6 shows an example of the number of new $P(t)$ and cumulative adopters $Y(t)$ over time according to a Bass model with $m = 5500$, $p = 0.025$, and $q = 0.25$. It shows three phases of new adopters, including the initial state, increasing, and decreasing stages. In the initial state, the number of previous adopters $Y(t)$ is close to 0 at $t = 0$, which indicates $P(t)$ is approximately equal to p . Therefore, the new adopters are mostly innovators at the beginning of the diffusion process. For the increasing stage, it is a combination of imitators and innovators, the number of adopters grows rapidly and reaches the highest at $t = 9$. After that, the new adoption slows down until it reaches the potential market.

Disaggregated analysis

We develop a discrete choice model to study the overall behavior response to the fare incentive. Also, we build a set of discrete choice models to study the heterogeneous behavior response of different types of adopters, including early/late, attrition/sustained, and early morning/late morning adopters. The discrete choice models are widely used in the transportation behavior modeling analysis and derived from the random utility maximization (Ben-Akiva and Bierlaire 1999; Chen et al. 2022).

A binary logit model (detailed in section "Disaggregated analysis") was used to estimate the probability of adopting the incentive as a function of various explanatory factors. Its coefficients can be used to quantify the factors contribution to the incentive adoption and the marginal rate of substitution (MRS) between variables, such as the MRS between fare savings and departure time changes (i.e., value of incentive times). The selected model variables should capture users' travel patterns in frequency, time,

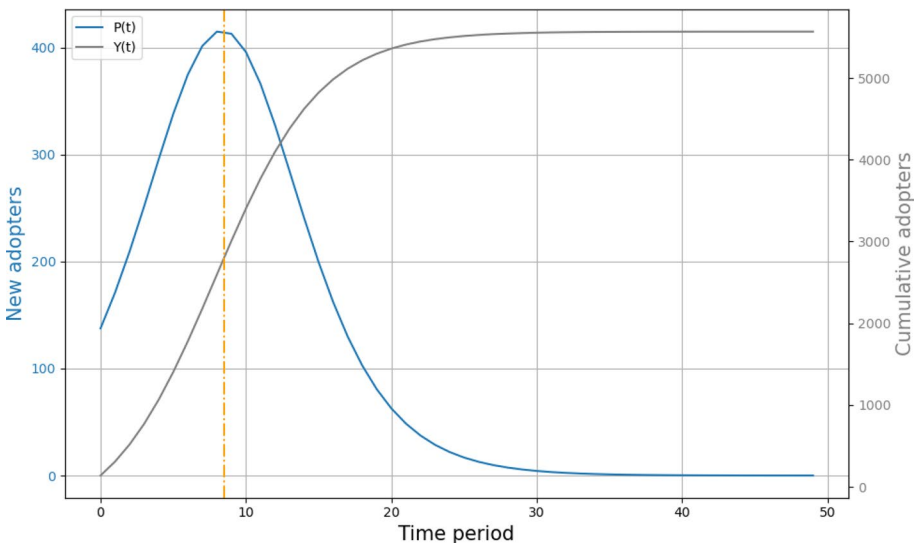


Fig. 6 Adopters versus cumulative adopters over time for the example Bass model

and space as they impact individuals' adoption behavior. The variables should measure how often they travel, when their trips take place, and their origin and destination, as well as the variability of these across days.

Table 1 summarizes potential variables that can be used in the adoption behavior modeling analysis, their definitions, and behavioral proxies (see Basu (2018) for a detailed discussion of these variables). The variables are calculated for each user based on their AFC activities in two months before the implementation of the promotion policy (i.e., July 2014 and August 2014 in the case study).

Case study

Adopter identification

We used Eqs. 2 and 3 to identify adopters and their adoption/attrition dates by setting the following parameters: $K = 8$, $j = 20$, $\beta = 0.3$. $K = 8$ means that 8 change points were detected for each passenger in the studied period (i.e., 18 months). $j = 20$, $\beta = 0.3$ mean that we associate the identified passengers' behavior changes to the incentive if they conduct 30% more trips out of 20 trips within the promotion period after the behavior change point than those in July–August 2014. It is robust to passengers' random departure times across days. We identified adopters starting from September 1st, which is the first day that the program was officially launched. The post refinement process further excludes the potentially 'fake' adopters caused by seasonal mobility fluctuation and lifestyle or work location changes. To do these, we compared individuals' mobility pattern of the above identified adopters between September 2014 and September 2015. Specifically, if a passenger has 30% more trips within the promotion period in September 2014 than in July–August 2014 and also 30% more promotional trips in September 2015 compared to July–August 2015, then these adopters (identified from Eq. 2) will be considered as seasonal changes and excluded from the adopter set. In addition, for the refinement to exclude the influence of work changed, we remove adopters who change their origin or destination or both stations in the initially identified adopters. Finally, 3,070 adopters are identified for the longitudinal analysis (13.57% of the panel passengers).

Disaggregated analysis

Spatiotemporal adoption patterns

We calculate the ratio of different types of adopters in the identified adopter set. Compared to the early adopter (39.80%), there are more late adopters (60.2%) who adopted the promotion after two months of the program implementation. The morning peak adopter accounts for 80.95%, which is the target group of the pre-peak discount promotion program (spreading peak travels). As similar to the reported results in (Ma et al. 2020), a high percentage of adopters (45.5%) change back to their previous departure times in the long term, which may significantly impact the promotion program efficiency over time. From this analysis, we also find that there is a significant proportion of early morning adopters (19.05%) who change their departure times to take advantage of the fare discount but do not contribute to the program. This phenomenon indicates that this group may induce some negative effects on the effectiveness of the promotion strategy (e.g., inequality, new peak hour). Therefore,

Table 1 Explanatory variables, definitions, and proxies (adapted from Ma et al. (2020))

Variables	Definitions	Proxies
<i>Frequency</i>		
P_{active}	The percentage of weekdays that a user uses the system at least once (active) on that day over all weekdays	System dependency
$\mu_{Trips}, \sigma_{Trips}$	The mean and std of the number of trips per day	System usage
μ_{Pros}	The mean of the number of trips exiting at promotion stations per day	Promotion stations usage
μ_{Trips_m}	The average number of days with morning trips per week	Morning trip frequency
μ_{Trans_m}	The average number of transfers in morning trips per day	Morning trip convenience
<i>Time</i>		
$\mu_{First_{out}}, \sigma_{First_{out}}$	The mean and std of the completion time (destination station exit time) of the first morning trip in each day	Schedule flexibility measured by the std. Higher values indicate higher flexibility
$\mu_{Last}, \sigma_{Last}$	The mean and std of the completion time (destination station exit time) of the last trip in each day	
$\mu_{First_m}, \sigma_{First_m}$	The mean and std of tap-in time of the first morning trip on weekdays	
μ_{TripT}	The average travel time of morning trips on weekdays	Trip distance
<i>Space</i>		
μ_{RI}, σ_{RI_s}	The mean and std of the relative importance (RI) of all used stations	RI reflects user activity variability or travel flexibility in space
$P_{max}(RI_s)$	The percentage of trips that start or end at the station that a user visits most	
$\mu_{RI_{od}}, \sigma_{RI_{od}}$	The average and std of the relative importance (RI) of all traveled OD pairs	
I_{Home}	Inferred home location based on the station where most of a user's first trips start and last trips end	Home location
I_{Work}	Inferred work location based on the station where most of a user's first trips end and last trip starts	Work location
n_{Uniq_s}	The number of unique stations a user visits	System familiarity
$n_{Uniq_{od}}$	The number of unique OD pairs a user travels	Travel regularity
$\mu_{Uniq_s}, \sigma_{Uniq_s}$	The mean and std of the number of unique stations a user visits per day	
$\mu_{Home}, \sigma_{Home}$	The mean and std of the number of trips that begin or end at the inferred home station ¹ of the user per day	The centrality of trips around home

Table 1 (continued)

Variables	Definitions	Proxies
$\mu_{Symm}, \sigma_{Symm}$	The mean and std of the number of symmetric OD trips made per day	Flexibility in mode or station choices
$\mu_{Dist}, \sigma_{Dist}$	The mean and std of the total distance covered using the system per day	Activity variability
$\mu_{Disp}, \sigma_{Disp}$	The mean and std of the displacement (distance) between the origin station of the first trip of the day and the destination station of the last trip of the day	A large displacement indicates that a user may utilize other modes for return trips
<i>Incentive</i>		
μ_{Saving_m}	The expected fare savings associated with the incentive of the morning trip	Money savings (behavior change triggers)
μ_{TSuff}	The expected minimum time a traveler has to change to be eligible for the incentive	Minimum displacement time (inconvenience)

std standard deviation

understanding such travellers' responses to the promotion strategy is also insightful to help optimize existing promotion strategy and promote its equity. Note that the main consideration in selecting the promotion time period is to reduce the peak crowding by shifting peak travel to the promotion time period, while minimizing the fare revenue loss, by selecting a one hour promotion period in the off-peak rather than applying this from the start of the operating day (e.g., 'free before 7' program Melbourne). Please refer to (Ma et al. 2020) for more information on "how to optimize the existing promotion strategy".

Figure 7 shows the distribution of the average departure time change for different types of adopters. Note that the positive and negative values indicate early morning and morning peak adopters, respectively. Figure 7a shows the departure time change distribution between early and late adopters. Comparatively, the time change distribution of the early adopters is more concentrated than that of the late adopters. It indicates that early adopters are more sensitive to changing their routine departure times in order to take advantage of the fare discount. Figure 7b shows the time change distribution between sustained and attrition adopters. Compared to the early morning adopters, the morning peak adopters are more likely to reverse back to their previous behavior in a long term.

Figure 8a shows that the expected money saving is around 2.1 dollars with 95 percentile of adopters saving within 3.5 dollars. Figure 8b shows the expected money-saving distribution between early and late adopters. Comparatively, the money-saving distribution of the early adopters is more concentrated than that of the late adopters. The early adopters also, in average, save more than late adopters. Figure 8c shows the expected money-saving distribution between sustained and attrition adopters. Interestingly, more attrition adopters who save more than 3 HK dollars than that of sustained adopters. Figure 8d shows the expected money-saving distribution between early morning and morning peak adopters. Obviously, most of the early morning adopters save 0 to 2 dollars, while the morning peak adopters tend to save more dollars.

Figure 9 shows the heatmap of origin stations for early adopters (Fig. 9a) and late adopters (Fig. 9b), and the heatmap of destination stations for early adopters (Fig. 9c) and late adopters (Fig. 9d). The station is colored based on the ratio of adopters (the number of adopters using that station over the total number of adopters). Generally, the early and late adopters show a similar spatial distribution of the origin station, with trips starting centering around areas of New Territories and Kowloon. Compared to the early adopters, the late adopters' origin station distribution is relatively more diverse with more trips starting from distant areas to the designated promotion stations around the CBD. Both heatmaps

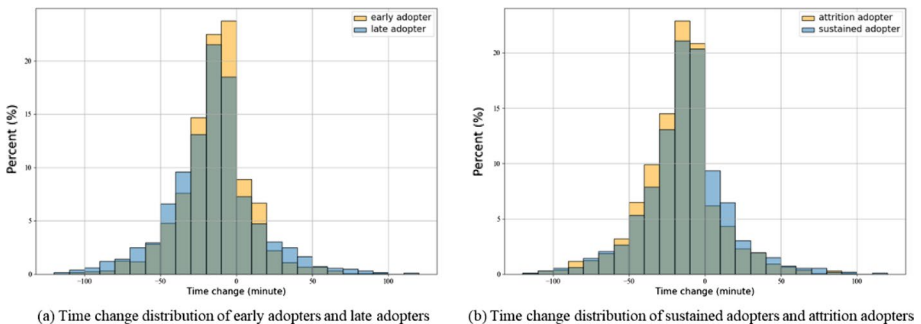


Fig. 7 The departure time change distribution among different types of adopters

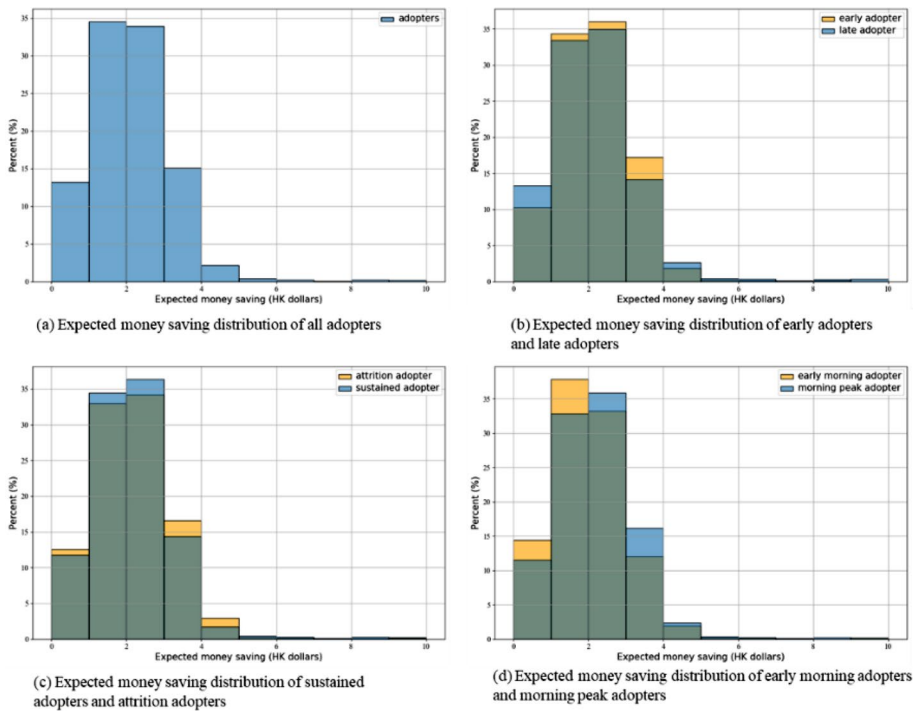


Fig. 8 The distribution of expected money savings of different type of adopters

of destination stations show a cluster pattern with a set of exit stations having more adopters than other stations. For example, the top 5 destination stations are HungHom, Central, Wanchai, and CausewayBay, and TsimShaTsui regardless of adopters.

Incentive diffusion process

We used the Bass model (Bass 1969) to explore the incentive diffusion dynamics in the studied population. Figure 10 shows the number of new adopters over time (unit of a month). The number of new adopters starts growing from the beginning and reaches its maximum in the second month. After that, the number of new adopters continuously decrease with some fluctuations at certain dates. We fit a Bass model to understand the diffusion process of the new adopters and forecast the total number of adopters.

The coefficients of the fitted Bass model (Eq. 4) are shown in Fig. 10. The total number of potential adopters is 3122 (13.80% of our panel passengers will change their travel behavior). This indicates that 98.3% of potential market of the promotion policy have shown after 16 months and there will be few new adopters afterwards. The innovation coefficient (0.1487) shows that every month, 14.87% of the remaining potential adopters will learn and shift from peak travels to off-peak given incentives (innovators). The imitation coefficient is 0.1%, which indicates that very few adopters adopt the promotion because of being influenced by other adopters (imitators). In other words, most of adopters adopt the promotion based on their own decision without other adopters' pressure. There is nearly no effect of word-of-mouth in the incentive diffusion. This could be as expected since the

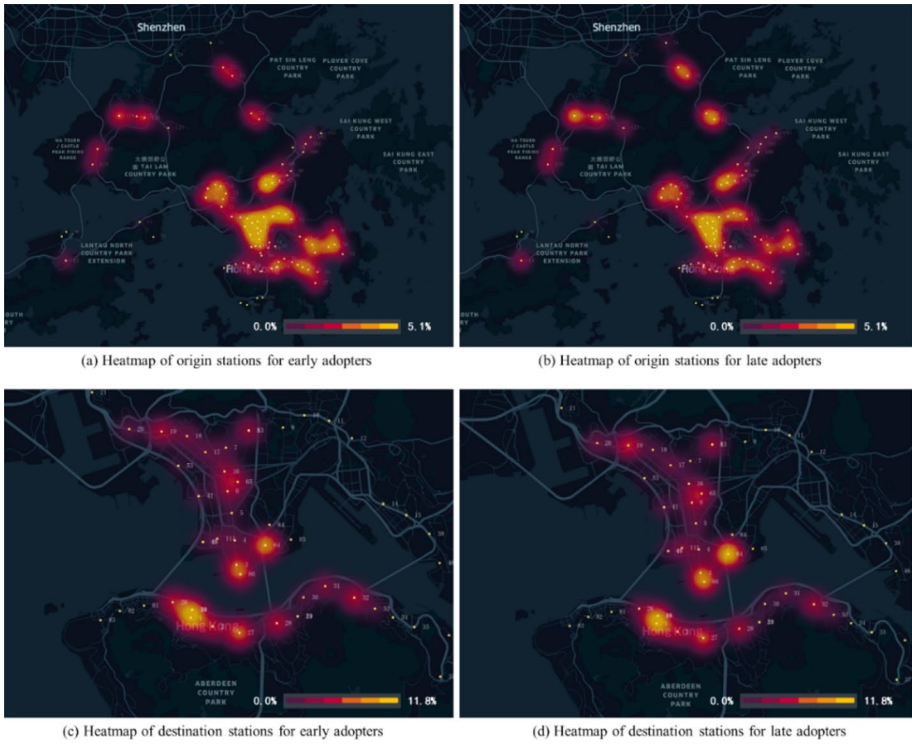


Fig. 9 The heatmap of ratio of adopters at origin and destination stations

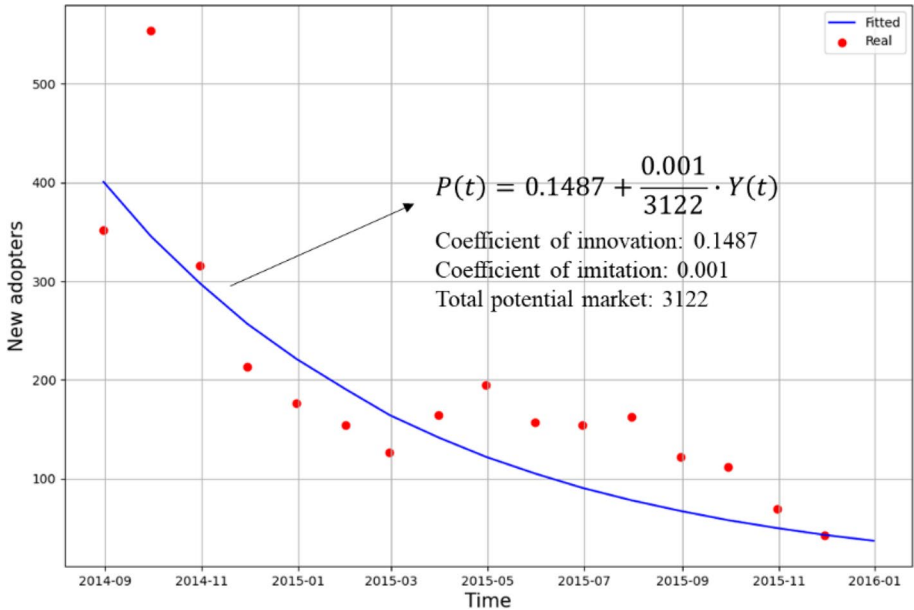


Fig. 10 The number of new adopters over time

promotion is not same as the commonly used product to meet every one’s demand and it is based on passengers’ own special travel pattern and flexibility.

Disaggregated analysis

Overall adoption choice modeling

To understand the factors that impact the adoption behavior of incentives (non-adoption and adoption), a binary logit model is estimated (the base in non-adoption). The following model specification best explains the adoption behavior after testing different model specifications (Table 1).

$$U_{adopter,i} = \beta_0 + \beta_1\sigma_{First_m} + \beta_2\mu_{TShift} + \beta_3\mu_{Svaing_m} + \beta_4I_{Work} + \varepsilon_{adopter,i} \tag{5}$$

$$U_{nonadopter,i} = 0 \tag{6}$$

where β_0 is the alternative specific constant, and β_1, \dots, β_4 is a vector of coefficients of the explanatory variables. ε captures the impact of all unobserved factors that affect the person’s choice.

Table 2 presents the estimation results. The Pseudo R² is 0.1017 which shows a good modeling performance, and the coefficients are reasonable given their signs. The significant factors for incentive adoption include: the standard deviation of departure times (flexibility), the minimum displacement time (inconvenience), the expected money saving (economic motivations), and the work location region. The alternative specific constant (ASC) of incentive adopters is negative, reflecting a low willingness to accept incentives to change departure times for travelers. Travelers with more flexible departure times are more likely to adopt incentives as they may have flexibility to change their work or study schedules. As expected, the higher the minimum displacement time to receive the incentive, the lower the probability of adopting the incentive. The more expected money savings, the more likely the passengers will adopt the incentive. The findings are consistent with the prior expectations and other findings in Beijing metro system (Wang et al. 2020) and Hong Kong system (Anupriya et al. 2020; Halvorsen et al., 2020a).

Table 2 Estimation results of incentive adopter (non-adopter is the base)

Explanatory variable	Coefficient	Z	P> z
Schedule flexibility (σ_{First_m})	0.0061	6.11	<0.001
Minimum displacement time (μ_{TShift})	-0.0378	-34.78	<0.001
Money savings (μ_{Svaing_m})	0.0721	3.81	<0.001
Work location (I_{Work})			
Hong Kong Island	0.2221	2.39	0.017
Kowloon	0.3055	3.28	0.001
New Territories	Base		
Constant	-0.9324	-8.69	<0.001
Number of observation	17,900		
LR Chi ²	1659.58		
Prob>Chi ²	<0.001		
Pseudo R ²	0.1017		

The incentive value of time (IncVOT, MRS between the minimum departure time changes and fare savings) for the adopter is 4.1 USD/hr, which is nearly one third of the value reported in Beijing (13.5 USD/hr) (Wang et al. 2020). That means travelers, who usually tap in/out stations with promotions policy in MTR systems, are more sensitive to the fare incentives (i.e., requiring less incentive to change one unit of departure time). The reason could be that the distance-based trip fare in Hong Kong (0.65–6.5 USD per trip) is much higher than that in Beijing (0.32–1.28 USD per trip). Note that the average exchange rate in 2014 (1 HKD ≈ 0.13 USD, 1 RMB ≈ 0.16 USD) is used. Compare to travelers who work in the New Territories region, those who work in Hong Kong Island and Kowloon are more likely to adopt incentives and change their departure times.

Choice models for different types of adopters

As discussed in section "Longitudinal, spatiotemporal adoption pattern", the incentive adopters are categorized into three paired groups based on their adoption timing and behaviors, including early/late adopters, early-morning/morning-peak adopters, and attrition/sustained adopters. To understand the heterogeneous impact of explanatory variables, we develop three multinomial logit models corresponding to these paired groups (the base is non-adopter). The utility functions for the early/late adopter are specified as:

$$U_{EA,i} = \beta_{0EA} + \beta_{1EA}\sigma_{First_m} + \beta_{2EA}\mu_{TShift} + \beta_{3EA}\mu_{Saving_m} + \beta_{4EA}I_{Work} + \varepsilon_{adopterEA,i} \quad (7)$$

$$U_{LA,i} = \beta_{0LA} + \beta_{1LA}\sigma_{First_m} + \beta_{2LA}\mu_{TShift} + \beta_{3LA}\mu_{Saving_m} + \beta_{4LA}I_{Work} + \varepsilon_{adopterLA,i} \quad (8)$$

$$U_{nonadopter,i} = 0 \quad (9)$$

The same utility specifications are applied for other two paired types of adopters, early-morning/morning-peak adopters, and attrition/sustained adopters. Table 3 shows the

Table 3 Estimation results of paired types of incentive adopters (non-adopter is the base)

Explanatory variable	EA	LA	EMA	MPA	AA	SA
Schedule flexibility (σ_{First_m})	0.0028 ^a	0.0081 ^c	0.0155 ^c	0.0034 ^c	0.0051 ^c	0.0069 ^c
Minimum displacement time (μ_{TShift})	-0.0483 ^c	-0.0319 ^c	-0.0390 ^c	-0.0376 ^c	-0.0372 ^c	-0.0384 ^c
Money savings (μ_{Saving_m})	0.0691 ^b	0.0738 ^c	-0.0084	0.0921 ^c	0.0844 ^c	0.0615 ^b
Work location (I_{Work})						
Hong Kong Island	0.3814 ^c	0.1232	-0.3484 ^a	0.3390 ^c	0.1887	0.2508 ^b
Kowloon	0.3205 ^b	0.2985 ^c	0.3051 ^a	0.3048 ^c	0.2883 ^b	0.3205 ^c
New Territories	Base					
Constant	-1.6064 ^c	-1.5991 ^c	-2.4849 ^c	-1.1727 ^c	-1.7125 ^c	-1.5456 ^c
Number of observation	17,900		17,900		17,900	
LR Chi ²	1735.92		1767.91		1662.03	
Prob > Chi ²	<0.001		<0.001		<0.001	
Pseudo R ²	0.0850		0.0917		0.0810	

EA: Early Adopter; LA: Later Adopter; EMA: Early Morning Adopter; MPA: Morning Peak Adopter AA: Attrition Adopter; SA: Sustained Adopter

^aP < 0.1, ^bP < 0.05, ^cP < 0.01

estimation results for pairwise adopters (the base is the non-adopter). The results interpretation are for paired types of adopters. For early and late adopters, passengers with more flexible habitual departure times are more likely to be early adopters. The main reason could be that passengers with more flexible schedule are more willing to try new products (incentives). Passengers who need to change more habitual departure times are less likely to adopt earlier. In addition, passengers who are expected to save more money tend to adopt the incentive relatively late. The main reason could be that long-distance travelers are less likely to adjust their schedules easily due to the complexity of their travel activities. Passengers working in Hong Kong Island and Kowloon regions are more willing to adopt the incentive early.

For early morning and morning peak adopters, morning peak adopters are more sensitive to the required change in departure time and money savings. Also, the work location region of travelers is significantly associated with incentive adoption behaviors. For attrition and sustained adopters, sustained adopters are more sensitive to the schedule flexibility but less on the money savings. Passengers working in Hong Kong Island and Kowloon regions are more likely to sustain their behavior changes. The IncVOT for early and late adopters are 5.59 USD/hr VS 3.38 USD/hr, respectively. The IncVOT for morning peak adopters is 3.25 USD/hr. The IncVOTs for attrition and sustained adopters are 3.38 USD/hr and 4.94 USD/hr, respectively. The IncVOTs for different adopter groups are insightful for agency to encourage more personalized promotion strategies and thus enhance the equity and sustainability of such fare policy.

Conclusions

To address crowding, many public transport agencies implemented promotion-based demand management strategies to facilitate better utilization of the available capacity of existing systems. Though several studies explore passengers' behavioral responses to the promotion, they focus on short-term adoption behavior and limited study is reported on the longitudinal analysis of the passenger adoption behavior. The paper comprehensively analyzes and models the longitudinal behavior of passengers under incentives using a large-scale AFC dataset from Hong Kong, with a special focus on the heterogeneity among different types of adopters. We also propose a robust approach to automatically identify adopters and their corresponding adoption and attrition dates using the time-series break point detection method.

Case studies show that 19.05% of adopters are not the program-targeted passengers whose adoption cannot impact the crowding in peak periods. The longitudinal analysis shows that early adopters have a more concentrated distribution of both time change and expected money saving than that of the late adopters. Compared to the early morning adopters, the morning peak adopters have a bigger attrition rate, which is not desired by the incentive program. The morning peak adopters can save more expected money than early morning adopters. The spatial analysis shows that the early and late adopters share similar origin and destination distributions, however, the late adopters have a more diverse origin station distribution. The diffusion modeling shows that the word-of-mouth effect is marginal and most adopters are innovators.

The choice modeling analysis highlights important factors influencing passengers' adoption behavior: the standard deviation of departure times (flexibility), work location region, the required change in departure time (inconvenience for changes), and the expected money

saving (monetary trigger). The incentive value of time (IncVOT) for the overall panel adopters is 4.1 USD/hr, and it varies across different types of adopters. Generally, the late and attrition passengers are more sensitive to the incentive levels. There could be potential to target incentivizing the late and attrition users in the long term or improving the information distribution channel to these groups of people (speeding the information diffusion).

The findings provide useful insights for agencies to design a more personalized and equitable promotion scheme for travelers. However, as common to empirical transport studies, the interpretation of findings is valid for the studied case in Hong Kong. It provides an evidence-based policy analysis for the incentive program in the Hong Kong context, an important secondary data source for the meta-analysis of the literature to develop generalizable conclusions from different cities and countries. Note that, the paper focuses on the longitudinal adoption pattern analysis of different types of adopters and develop discrete choice models to model adoption behavior as a set of explanatory variables extracted from AFC data. Future work will explore more advanced choice modeling techniques to model the longitudinal adoption process of individual passengers (e.g., dynamic choice modeling).

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Availability of data and materials The datasets generated and analysed during the current study are available from the corresponding author on reasonable request.

Declarations

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

Ethical approval Not applicable.

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