Wearable fitness trackers and smartphone pedometer apps: Their effect on transport mode choice in a transit-oriented city

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Abstract

Shifting travel demand from motorized to non-motorized modes has been considered as an effective approach to addressing numerous urban transportation problems, including traffic congestion, road accidents, and noise and air pollution. Walking has been commonly promoted by governments and non-governmental organizations all over the world, predominately due to a wide array of its health, environmental, economic, and social benefits to individuals and society. With the rapid developments of wearable fitness trackers and smartphone pedometer apps in recent years, people have paid more attention to their physical health by heart rate, fitness, and sleep tracking. Recent studies have confirmed their contribution to promoting walking, but there has been a lack of research examining their influence on people's transport mode choice. In this study, we randomly interviewed 505 people in Hong Kong, an example of a transit-oriented city, in an interviewer-administered face-to-face interview survey. A series of binary logit models are calibrated to determine factors that significantly affect people's selection of walking and traveling by public transport. The results show that the users of wearable fitness trackers and smartphone pedometer apps generally preferred a transport mode with more walking steps than the non-users. People preferred traveling by public transport and getting off at a station earlier followed by walking, in which the marginal effects of every additional 100 steps are 6.31% and 1.78% on the selection probabilities for the users and non-users, respectively. Some transport policy measures are suggested and discussed accordingly to promote walking.

Keywords: wearable fitness trackers, smartphone pedometer apps, walking behavior, binary logit model, stated preference survey, first preference recovery.

1. Introduction

Shifting travel demand from motorized to non-motorized modes (mainly comprised by walking and cycling) has been deemed as one of the effective approaches to addressing numerous urban transport problems, including traffic congestion, road accidents, noise, and air pollutions (Cervero and Kockelman, 1997; Woodcock et al., 2009; Ewing and Cervero, 2010; Keall et al., 2018; Singleton, 2019; Stefansdottir et al., 2019). Evidently, cycling is beneficial to individual health and the environment (Rérat, 2019; Heinen et al., 2010). However, it is restrained by provisions of bikes, parking spaces, and cycling tracks as well as the riding ability of individuals. Comparatively, walking has higher flexibility and is more applicable for a transit-oriented city (e.g., Hong Kong, Singapore, and London) where provides more frequent and relatively reliable public transport services (Land Transport Authority, 2012; Lu et al., 2017). Predominately attributed to the pedestrian-friendly and walkable environment, most of the amenities (e.g., shopping centers, transit, and schools) in Hong Kong are more accessible on foot than its car-dominated counterparts such as cities in the United States, Canada, Australia, and New Zealand (Guo and Loo, 2013; Cole et al., 2017). Most of the local people have a habit of walking with the average daily walking step of 6,880, which tops in the global ranking (Althoff et al., 2017). In such a context, cycling may only be suitable for recreation and leisure purposes in holidays but not for daily commutes.

As an environment-friendly and sustainable non-motorized transport mode, walking has drawn substantial scholarly attention in recent years (e.g., Wasfi et al., 2016; Lee and

Dean, 2018; Yang et al., 2018; Anciaes et al., 2019; Battista and Manaugh, 2019). It is easily incorporated into a daily routine and has proved to provide a wide array of health, environmental, economic, and social benefits to individuals and the society as follows: (1) walking is the most prevailing aerobic exercise that offers a range of health benefits to individuals, including improvements in cardiovascular and mental health, as well as a decreased risk of numerous diseases such as depression and obesity (Manson et al., 1999; Pucher and Dijkstra, 2003; Lee and Dean, 2018; Lee et al., 2019). In addition, it also provides improvements in quality of life and subjective wellbeing (Bird et al., 2013); (2) environmental benefits of walking include but are not limited to decreasing automobile use, alleviating noise and air pollution, and reducing greenhouse gas emissions (Woodcock et al., 2009); (3) walking also contributes to consumer cost savings (e.g., reducing fuel cost and travel fare) and public cost savings (e.g., alleviating traffic congestion, and shortening travel time) (Litman, 2003); and (4) walking indeed has quite a few social benefits to encourage social interaction, and boosts community cohesion, trust, and liveability (Lund, 2002; Leyden, 2003; du Toit et al., 2007; Pivo and Fisher, 2011). All in all, walking provides substantial benefits. It is recommended to promote walking in the community to improve public health and the environment.

With the rapid developments of wearable fitness trackers (WFTs) and smartphone pedometer apps (SPAs) in recent years, people have paid more attention to their physical health by heart rate, fitness, and sleep tracking. Pedometers were originally invented to count walking steps by detecting the motion of individuals, the concept of which can be traced to Leonardo da Vinci (Gibbs-Smith, 1978). Nowadays, pedometers have been integrated into various portable electronic devices, such as smartphones, music players, and watches (e.g., FitBit and Apple Watch). People can easily use pedometer-integrated fitness apps (e.g., WalkLogger and WeChat Exercise) on their smartphones for tracking their physical activities (Aittasalo et al., 2012; Conroy et al., 2014; Fong et al., 2016). Apart from counting steps, these devices have much more advanced functions, including goal setting, fitness and health tracking, and self-monitoring (Sullivan and Lachman, 2017). For instance, they have proved to provide incentives for walking or participating in other physical activities (Bravata et al., 2007; Sullivan and Lachman, 2017). With the increasing penetration rate of these devices, the use of the pedometer feature will become more popular.

Numerous studies, mainly from public health and transportation planning fields, have pointed out that WFTs and SPAs can be used to motivate and encourage participating physical activities, measured by a multitude of indicators (e.g., daily step count and 6-min walking distance). Chan et al. (2004) observed that a pedometer-based intervention significantly motivated the physical activities of sedentary office workers. By adopting a 6-week randomized controlled trial, Araiza et al. (2006) proved the effectiveness of a pedometer-based program in promoting the physical activity of patients with type 2 diabetes mellitus. Snyder et al. (2011) revealed that the pedometer was a successful motivational tool to enhance the physical activity level in old ambulatory adults. Using a randomized controlled trial, Mendoza et al. (2015) suggested that pedometer use could effectively encourage patients with chronic obstructive pulmonary diseases to increase their frequency of physical activities and improve their quality of life. Thorup et al. (2016) found that cardiac patients' motivation considerably increased with pedometer use. Fong et al. (2016) demonstrated that SPAs provided larger benefits in enhancing the level of physical activity for old adults than traditional pedometers. Bravata et al. (2007) performed a meta-analysis to estimate the effect size and confirmed the association of pedometer use with participation in physical activities among adults. However, there are still a few studies that questioned the effect of pedometer use on physical activity uplift. For example, Eastep et al. (2004) found that the motivation effect of pedometers was marginal for 26 participants and indicated that the effect exists only with goal setting. Butler and Dwyer (2004) suggested that pedometer use does not significantly affect the walking step counts of 32 participants aged between 45 and 65 years.

Although most of the abovementioned studies have agreed with the substantial contributions of WFTs and SPAs to promote walking, there has been a lack of comprehensive research on the influence on the transport mode choice of their users. The majority of studies concerning correlates of transport mode choice focused on socio-demographic (e.g., age, sex, educational attainment, and car availability) and physical environment characteristics (e.g., population density, land-use diversity, street connectivity, and parking/sidewalk availability) (Brownson et al., 2009). It is still unknown to us about the effectiveness of WFTs and SPAs in changing people's travel decisions. Do the users and non-users behave significantly differently in opting for transport modes? What kind of situations affects their willingness-to-walk? These are what this study attempts to answer.

To answer these questions, a stated-preference survey was conducted in October and November 2017 to interview 505 people in Hong Kong, an example of a transit-oriented city, in which the respondents were presented with two given transport mode choices (i.e., (1) either traveling by public transport or walking to the destination, or (2) both) in four hypothetical situations (two for a short trip and the other two for a long trip) and asked for their preference of transport mode. Based on a total of 2,020 observations, a series of binary logit models were developed to identify factors that significantly influence people's transport mode choice. Market segmentation analysis was conducted to examine the variations in travel decisions of users and non-users of WFTs and SPAs in short and long trips. In addition, model validation was carried out to confirm the models' performance. This paper also suggests and discusses some transport policy measures to promote walking.

The remainder of this paper proceeds as follows. Section 2 presents the respondents' socio-demographic profiles and depicts the walking habits of WFTs and SPAs users. Section 3 describes the formulation of binary logit models, and the methodologies for market segmentation analysis and model validation. Section 4 presents the model results. Section 5 recommends transport policy measures to promote walking. Section 6 concludes the paper and suggest directions for future study.

2. Data

2.1 Data Collection

An interviewer-administrated face-to-face questionnaire survey was conducted in October and November 2017 during the daytime and at night. Seven residential and commercial districts in Hong Kong, including Central, Causeway Bay, Tsim Sha Tsui, Mong Kok, Kwun Tong, Tsuen Wan, and Sha Tin were selected for the survey to interview people with diverse backgrounds to prevent sampling bias. Our surveyors randomly approached the potential interviewees on streets and interviewed them after obtaining their verbal consent to conduct the survey. We read the questions aloud, asked for their travel decisions in four hypothetical games, and filled in the questionnaires with only closed questions. It took around 5 minutes to complete one questionnaire. No special events or incidents, which may potentially ruin the quality and reliability of the survey data, occurred during the survey period.

The questionnaire used in this study comprised three parts: (1) socio-demographic characteristics of the respondents (e.g., gender, age, and use of WFTs and SPAs); (2) walking habits of the WFTs and SPAs users (who were using or regularly used before); and (3) stated preference questions in four hypothetical scenarios for their transport mode choice of either traveling by public transport or walking, or both for going home. We successfully interviewed 505 people and thus collected 2,020 observations. Based on the pragmatic decision, 1,616 observations from 404 respondents (80% of the collected data) were randomly selected from the samples for model estimation, and the rest were reserved for validation at a later stage. The sample size was considered sufficient to estimate a well-behaved model in a stated choice experiment (Suzuki et al., 2002).

2.2 Socio-demographic distribution of the respondents

Table 1 tabulates the socio-demographic profiles of the 505 respondents. The gender was almost evenly distributed, while 59% were male and 41% were female. The samples covered a board spectrum of respondents in different age groups, while around 53% of them were between 18 and 34 years old. A large proportion of them (86%) did not own a private car for family use. This figure is fairly consistent with that provided by the traffic census of 85.6% (Transport Department, 2014). As a transit-oriented city, the majority of Hong Kong people were regarded as frequent transit users, who either walked or traveled by public transport, or both for their daily journeys (Szeto et al., 2017; Wong et al., 2017). Over 31% of the respondents reported that they regularly used before or they were using WFTs and SPAs for tracking their physical activities. It is observed that the use of WFTs and SPAs among the general public was still low in Hong Kong.

Table 1. Respondents' socio-demographic profiles

Personal particulars	Groups	Frequency (percentage) [Sample size = 505]
Gender	Male	298 (59.0%)
	Female	207 (41.0%)
Age	Below 18 years	81 (16.0%)
	18-21 years	141 (27.9%)
	22-34 years	125 (24.8%)
	35-44 years	69 (13.7%)
	45-54 years	43 (8.5%)
	55 years or above	46 (9.1%)
Car availability for family use	Yes	71 (14.1%)
	No	434 (85.9%)
Use of wearable fitness trackers and smartphone pedometer apps	Using continuously	86 (17.0%)
	Used before/using periodically	72 (14.3%)
	Did not use before	347 (68.7%)

2.3 Walking habits of wearable fitness trackers and smartphone pedometer apps users

Table 2 shows the walking habits of the 158 users who regularly used WFTs and SPAs before or they were using these devices. The majority of them (38%) used these devices for less than six months, while about 20% of them had been continuously using these devices for over 1.5 years. It is noted that over 40% of the respondents agreed that WFTs and SPAs encouraged walking more. The majority of the respondents (42%) reported that they walked for 8,001–12,000 steps every day on average, and only 10% walked less than 4,000 steps in a day. Only 30% of the respondents could achieve their daily targets of walking steps, and 57% of them did not even preset a target in their devices. The top prioritized factor adversely affecting the decision of walking to achieve the target was insufficient spare time, and this might be due to the busy lifestyle of Hong Kong people. In addition, slightly more than half of the respondents claimed that their walking decisions were restricted by the present physical and weather conditions.

Table 2. Walking habits of wearable fitness trackers and smartphone pedometer apps users

Walking habits	Groups	Frequency (percentage) [Sample size = 158]
Duration of use	Less than 0.5 year	60 (38.0%)
	0.5-1 year	41 (25.9%)
	1-1.5 years	21 (13.3%)
	1.5-2 years	18 (11.4%)
	More than 2 years	18 (11.4%)
Incentive to walk more using wearable fitness trackers and smartphone pedometer apps	Disagree	44 (27.8%)
	Neutral	50 (31.6%)
	Agree	64 (40.5%)
Daily average number of walking steps	4,000 steps or below	15 (9.5%)
	4,001-8,000 steps	47 (29.7%)
	8,001-12,000 steps	67 (42.4%)
	More than 12,000 steps	18 (11.4%)
	Did not record	11 (7.0%)
Achieve the daily preset target of walking steps	Usually yes	47 (29.7%)
	Usually no	21 (13.3%)
	Did not set a target	90 (57.0%)
Factors affecting the decision of walking to achieve the target (could be more than one answer)	Time of day	49 (31.0%)
	Weather condition	80 (50.6%)
	Air quality	36 (22.8%)
	Present physical condition	81 (51.3%)
	Spare time for walking	87 (55.1%)
	Present dressing	26 (16.5%)
	Walking environment	21 (13.3%)

2.4 Stated-preference questions

It is hypothesized that people's transport mode choice is mainly affected by in-vehicle travel time and fare of public transport, walking time, and the number of walking steps. The first three attributes have been commonly adopted in many other travel behavioral studies (e.g., Szeto et al., 2016; Golshani et al., 2018). The key element additionally incorporating in this study was the number of walking steps for the walking-related options. Walking time and the number of walking steps are not necessary to be directly proportional, as people may walk faster (with a shorter walking time) to achieve their daily target of walking steps. This assumption better simulates the lifestyle of Hong Kong people, who have long working hours and have no time in participating in physical activity (Abdullah et al., 2005; Wong, 2009). Furthermore, it is expected that transport mode choice may vary for different trip lengths. Our questionnaire survey addressed this problem for market segmentation analysis. Figure 1 shows an example of the choice set in the stated preference survey.

Please tick as appropriate.

Assume that you are going back to home under a favorable condition for walking (e.g., you may walk along a flat walkway at a moderate temperature on a sunny day), please select the most preferred option in the following independent games:

For a short trip within a walkable distance	Transport mode	Selection
	Travel by public transport for 12 minutes and pay a fare of $2	☐
	Walk for 19 minutes with 1600 steps	☐

For a long trip that requires to take a motorized transport	Transport mode	Selection
	Travel by public transport for 22 minutes and pay a fare of $11	☐
	Travel by public transport for 19 minutes and pay a fare of $7, get off at a station earlier followed by 10 minutes walking with 900 steps	☐

Figure 1. Example of a choice set in the stated preference survey

The respondents were required to decide either traveling by public transport or walking in the whole trip for a short trip; and decide either traveling by public transport or traveling by public transport first and getting off at a station earlier followed by walking in the partial trip for a long trip. The walking distance of a station of public transport (e.g., franchised buses or railways) is normally around 500 m in urban areas. Therefore, the required walking steps for the partial trip in the latter case were assumed to be fewer than that for the whole trip in the first case. In total, four hypothetical games (two for a short trip and the other two for a long trip) were presented, in which respondents were supposed to opt for one transport mode out of two to go back home. According to the findings in Section 2, the weather and physical conditions and other external factors may also influence people's intention to walk. For simplicity, we assumed that the respondents might walk under a suitable and comfortable walking condition.

Table 3 presents the 3-level attributes for different transport mode choices in the stated preference survey. All the attributes had three levels for capturing possible non-linear effects. As in our pilot survey, very limited respondents would select a walking option if it required more than 2,000 walking steps. Therefore, the number of walking steps in the hypothetical games were set at acceptable levels ranging from 700 to 1,600 steps. Having too wide an attribute level range may result in choice tasks with dominated alternatives, whereas having too narrower a range may result in respondents having trouble distinguishing alternatives (Ortuzar and Willumsen, 2011). The same approach was also applied to other attributes, in which the values were designed mainly based on the respondent's acceptance level as obtained in the pilot survey.

Table 3. Attributes and levels used in the stated preference questions

Trip length	Transport mode	Attribute	Levels
Short trips	Travel by public transport	Travel time (min)	10; 12; 14
		Travel fare (HK$)	2; 4; 6
	Walk	Walking time (min)	15; 17; 19
		Number of walking steps ('00)	12; 14; 16
Long trips	Travel by public transport	Travel time (min)	20; 22; 24
		Travel fare (HK$)	10; 11; 12
	Travel by public transport, get off at a station earlier followed by walking	Travel time (min)	15; 17; 19
		Travel fare (HK$)	7; 8; 9
		Walking time (min)	10; 12; 14
		Number of walking steps ('00)	7; 9; 11

The orthogonal fractional factorial design, a subset of a full factorial design, was used to decrease the size of the experiments while capturing the main effects of the attributes. The statistical and data analysis software package Minitab was adopted to generate 54 combinations of hypothetical games involving the above four attributes in the two cases of different trip lengths. They were randomly distributed into 14 sets of questionnaires. Prior to the main survey, the combinations of attribute settings for each experimental run were repeatedly and carefully reviewed to guarantee their feasibility and prevent unrealistic situations. A pilot survey was also conducted to test the experimental procedure.

3. Methodology

3.1 Binary logit model

Based on the assumption that each respondent makes the decision to maximize his/her overall utility, a binary logit modeling approach is used to describe their travel behavior based on the above explanatory variables. This modeling form has been commonly applied in numerous travel behavioral studies (e.g., Alemia et al., 2018; Wong et al., 2020). The model takes the following form (McFadden, 1974).

$$P_q^m = \frac{\exp\left(V_q^m\right)}{\sum_n \exp\left(V_q^n\right)}, \tag{1}$$

where m is the index of transport mode (i.e., either traveling by public transport or walking, or both); P_q^m is the probability that individual q decides to select mode m; and V_q^m is the deterministic utility incorporating the factors influencing the mode choice decision of individual q.

It is important to determine an appropriate utility functional form for the binary logit model. The process started with a simple model including the mode-specified attributes and constant. The utility function is written as follows.

Utility function (1):

$$V_q^m = \beta_q^{\mathrm{T}} T + \beta_q^{\mathrm{F}} F + \beta_q^{\mathrm{W}} W + \beta_q^{\mathrm{S}} S + \gamma, \tag{2}$$

where T, F, W, and S are the travel time, the travel fare, the walking time, and the number of walking steps, respectively. β_q^{T}, β_q^{F}, β_q^{W}, and β_q^{S} are the associated model coefficients; and γ is the model constant for the walking option which describes the overall perception of walking.

To additionally capture the different perceptions on the walking steps of the users and non-users of WFTs and SPAs, we segmented the respondents and β_q^{S} is hence expanded to $\left[\theta_q^{\mathrm{U}}\alpha_q^{\mathrm{U}} + \left(1-\theta_q^{\mathrm{U}}\right)\alpha_q^{\mathrm{N}}\right]$. The utility function is written as follows.

Utility function (2):

$$V_q^m = \beta_q^{\mathrm{T}} T + \beta_q^{\mathrm{F}} F + \beta_q^{\mathrm{W}} W + \left[\theta_q^{\mathrm{U}}\alpha_q^{\mathrm{U}} + \left(1-\theta_q^{\mathrm{U}}\right)\alpha_q^{\mathrm{N}}\right] S + \gamma, \tag{3}$$

where θ_q^{U} is a dummy variable, which equals 1 if the individual q is a WFT and SPA user, and 0 otherwise; α_q^{U} and α_q^{N} are the associated model coefficients to be estimated; and other notations are the same as those in Equation 2.

The best utility function was determined based on the Bayesian information criterion (BIC) evaluation. It is noted that the model with the lowest BIC value is the most preferable as it has the best fit to the data or involves the fewest explanatory variables, or both.

3.2 Likelihood ratio test

The market segmentation analysis for the variation in travel decisions for short and long trips was conducted by the likelihood ratio test (Watson and Westin, 1975). The test is based on the likelihood ratio, which is calculated by

$$L = -2\left(L_{\mathrm{R}} - L_{\mathrm{U}}\right), \tag{4}$$

where L_{R} is the log-likelihood of the base model, and L_{U} is the sum of the log-likelihoods of the corresponding individual models for short and long trips. The null hypothesis that there is no intervention in segmentation in trip length is rejected when the test statistic exceeds the threshold value specified in the chi-squared distribution at a chosen level of significance. The degree of freedom is calculated as the difference between the number of explanatory variables in the combined model and the sum of the number of individual models.

3.3 Model validation

To gain confidence in the models' performance and ensure their prediction accuracy, this study used 20% of the collected samples to validate the two developed sub-models. The model validation was based on the concept of first preference recovery (FPR) (Ortuzar and Willumsen, 2011) — a measure that presents the proportion of respondents who effectively select the option with the greatest modeled probability. It is equivalent to the percentage of choices correctly predicted according to the maximum utility classification. FPR has been used in a number of studies for model validation (Gunn and Bates, 1982; Wong et al., 2014) to compare the values of chance recovery (CR) and expected recovery (ER) and confirm that the model is both informative and reasonable.

CR is the proportion of the first preference choice given by the equally probable model. The CR value can be calculated as

$$\mathrm{CR} = \frac{1}{N}\sum_q \frac{1}{M_q}, \tag{5}$$

where N is the size of the validation sub-sample and M_q is the number of transport mode choices for individual q in the stated preference survey.

ER is the expected proportion of FPR estimated from the binary logit model over the validation sub-sample N. The ER value can be calculated as

$$\mathrm{ER} = \frac{1}{N}\sum_q P_q^{\max}, \tag{6}$$

where $P_q^{\max}$ is the maximum predicted probability associated with respondent q's best option, which is the estimated probability assigned to the first preference option.

Since FPR is an independent binomial random event for the individual q, the standard errors of CR and ER are

$$\mathrm{SE}\left(\mathrm{CR}\right)=\frac{1}{N}\sqrt{\sum_{q}\frac{1}{M_q}\left(1-\frac{1}{M_q}\right)} \text{ and} \tag{7}$$

$$\mathrm{SE}\left(\mathrm{ER}\right)=\frac{1}{N}\sqrt{\sum_{q}P_q^{\max}\left(1-P_q^{\max}\right)}. \tag{8}$$

Model validation involves the following null hypotheses: (1) there is no difference between the values of FPR and CR. If the test statistic exceeds the threshold value that is specified for the normal distribution at the chosen level of significance, we reject the hypothesis that the value of FPR is equal to that of CR and conclude that the model is informative; and (2) there is no difference between the values of FPR and ER. If the test statistic does not exceed the threshold value that is specified for the normal distribution at the chosen level of significance, we do not reject the hypothesis that the value of FPR is equal to that of ER and conclude that the model is reasonable.

4. Model results and discussion

A logit modeling software NLOGIT was used in this study, which uses the maximum likelihood estimation method to estimate the coefficient associated with each of the explanatory variables. Table 4 tabulates the results of the models with the two proposed utility functional forms. From the results of the logit model with utility function (1), most of the variables are significant at the 1% level, except the walking time. The coefficients of the first three attributes (i.e., the travel time, the travel fare, and the walking time) are all negative, which means that these attributes are negatively perceived by the respondents. That is, they preferred an option with a shorter time and lower fare required. In contrast, the coefficient of the number of walking steps is positive, which means that the respondents preferred walking for more steps. The constant term is negative, which implies that the respondents had a preference for not walking in general.

To further examine whether WFTs and SPAs influence the transport mode choice and the walking behavior of their users, utility function (2) segments the respondents into two groups: the users and the non-users. The results show that the coefficient magnitude of the number of walking steps is larger for the users of WFTs and SPAs (0.195) than their counterpart (0.101). This is reasonable since the number of steps should be attractive to the users and it helps the users to achieve their targets for walking steps. It echoes the findings of Alley et al. (2016), who indicated that people with fitness trackers are more concerned with their walking steps. A possible explanation is that the users have already developed their habit of achieving the daily target of walking steps. It matches with the observation that more than 40% of the respondents strongly agreed that these devices can provide them an incentive to walk more as presented in Table 2.

The BIC value decreases from 1.178 for utility function (1) to 1.153 for utility function (2) when one additional explanatory variable is added into the utility function. It presents the incremental benefit of introducing an additional explanatory variable into the base model. Therefore, utility function (2) is better and selected for further model development.

Table 4. Coefficients and their t-statistics for the binary logit models for all trip lengths

Explanatory variable		Coefficient [t-statistic]	
		Utility function (1)	Utility function (2)
Travel time (min)		-0.191[a] [-7.8]	-0.197[a] [-7.9]
Travel fare (HK$)		-0.115[a] [-3.0]	-0.119[a] [-3.0]
Walking time (min)		-0.024 [-0.8]	-0.028 [-0.9]
Number of walking steps ('00)	Users of wearable fitness trackers and smartphone pedometer apps	0.109[a] [3.6]	0.195[a] [5.8]
	Non-users of wearable fitness trackers and smartphone pedometer apps		0.101[a] [3.3]
Constant		-3.193[a] [-9.8]	-3.270[a] [-9.9]

Note: [a] Parameters are significant at the 1% level.

Table 5 shows the results of sub-models for different travel behavior on short and long trips. The results are similar to those of the base model as in Table 4. The most eye-catching difference is that the sign of the coefficients associated with the number of walking steps turns negative in short trips (-0.037 and -0.109). In this case, they have to walk for the whole trip. Notably, people tended to minimize the number of walking steps for both the users and non-users of WFTs and SPAs. However, the attribute is not significant particularly for the users of WFTs and SPAs, while statistical significance can be found for the non-users. This attribute has a weak correlation with the respondents' decisions.

For making a long trip that people may travel by public transport first and get off at a station earlier followed by walking for the partial trip, both the users and non-users demonstrate a strong positive preference for walking for more steps. The associated coefficients are 0.255 and 0.119 for the users and the non-users respectively. It could be explained that the required walking time and steps of this case (not more than 14 minutes and 1,100 steps as shown in Table 3) are more favorable and suitable for walking.

In addition, the constant terms for the two models are modest when compared with the products of mean value and coefficient of the five other attributes, which indicates that the models can effectively predict the transport mode choice of the respondents.

Table 5. Coefficients and their t-statistics for the binary logit models for short and long trips

Explanatory variable		Coefficient [t-statistic]	
		Utility function (2) for short trips	Utility function (2) for long trips
Travel time (min)		-0.145[a] [-3.0]	-0.073[c] [-1.9]
Travel fare (HK$)		-0.066 [-1.4]	-0.152[b] [-2.0]
Walking time (min)		-0.194[a] [-3.9]	-0.097[c] [-1.7]
Number of walking steps ('00)	Users of wearable fitness trackers and smartphone pedometer apps	-0.037 [-0.7]	0.255[a] [4.3]
	Non-users of wearable fitness trackers and smartphone pedometer apps	-0.109[b] [-2.2]	0.119[b] [2.2]
Constant		3.446[a] [2.8]	-2.281[b] [-2.5]

Note: [a] Parameters are significant at the 1% level. [b] Parameters are significant at the 5% level. [c] Parameters are significant at the 10% level.

Based on the model results, the marginal effects of the walking-related attributes to the respondent's willingness-to-walk were calculated and presented in Table 6. A marginal effect measures the change of the choice probability of an alternative in response to one unit increment in an independent variable (Zhao et al., 2020). It is noted that walking for the whole short trip is not favorable in general, and the marginal effects of walking time and the number of walking steps are all negative for both the users and non-users of WFTs and SPAs. On the other hand, for walking partially on a long trip, the marginal effects of every additional 100 steps are 6.31% and 1.78% on the selection probabilities for users and non-users, respectively. People tend to walk more in this case. The marginal effects of walking time are still negative (-2.34% and -1.35%), but their magnitudes are obviously smaller than those for short trips. The findings meet our expectation that people would like to walk faster (with a shorter walking time) for more walking steps.

Table 6. Marginal effects of the walking-related attributes

Explanatory variable		Utility function (2) for short trips	Utility function (2) for long trips
Users of wearable fitness trackers and smartphone pedometer apps	Walking time (min)	-2.82%	-2.34%
	Number of walking steps (‘00)	-0.51%	6.31%
Non-users of wearable fitness trackers and smartphone pedometer apps	Walking time (min)	-4.52%	-1.35%
	Number of walking steps (‘00)	-2.51%	1.78%

Table 7 tabulates the log-likelihood values of the combined model and the individual models for different trip lengths, which are used to calculate the likelihood ratio. Given that the degree of freedom is 6, the chi-square critical value at the 1% level is 16.81, which is lower than the likelihood ratio of 54.54. Therefore, the null hypothesis that there is no intervention in the segmentation of trip length is rejected. It is concluded that the individual models are different from each other and cannot be pooled. The associated mode choice decisions are different. Therefore, separate models are required.

Table 7. Results of the likelihood ratio test

Measures/conclusion		Result
Log-likelihood	Utility function (2) for all trip lengths	-909.39
	Utility function (2) for short trips	-484.65
	Utility function (2) for long trips	-397.47
Likelihood ratio		54.54
Chi-square critical value[a]		16.81
Conclusion of the likelihood ratio hypothesis test[b]		Reject

Note: [a] The chi-square critical value when the degree of freedom is 6 and the significance level is 0.01. [b] Null hypothesis tests at the 99% confidence interval.

Table 8 presents the model validation results. The FPR values for the models for short and long trips are 67.33% and 79.21%, respectively, indicating that more than two-thirds of the observations from the validation sub-sample selected the transport mode to which the calibrated model assigns the greatest probability. The FPR values also are beyond 3 standard errors from the corresponding mean CR. Hence, the first null hypotheses for both the sub-models are rejected, confirming that these models are informative. Moreover, the FPR values lie within 2 standard errors from the mean ER calculated from the developed choice models. Therefore, we do not reject the second null hypotheses that there is no difference between FPR and ER in the two sub-models, which indicate that the developed models are reasonable and confirm that the validation sub-samples are consistent with the model. We can thus conclude that the developed sub-models for short and long trips are both informative and reasonable, and have the capability to explain the data variation well.

Table 8. Results of model validation

Measures/conclusion	Utility function (2) for short trips	Utility function (2) for long trips
First preference recovery	67.33%	79.21%
Chance recovery	50.00%	50.00%
3 standard errors (%)	10.55%	10.55%
Conclusion of chance recovery hypothesis test[a]	Reject	Reject
Expected recovery	68.51%	78.35%
2 standard errors (%)	6.36%	5.65%
Conclusion of expected recovery hypothesis test[b]	Do not reject	Do not reject

Note: [a] Null hypothesis tests at the 99% confidence interval. [b] Null hypothesis tests at the 95% confidence interval.

5. Recommended transport policy measures

The results confirmed that WFTs and SPAs take a positive role in promoting walking, and consequentially improving public health. The Hong Kong government and non-governmental organizations may consider organizing some events and campaigns to encourage people using WFTs and SPAs, and sharing their walking records with their friends in social media (e.g., Instagram and Facebook). It has been proved effective to increase physical activity in young women by offering a social support group in social media (Rote et al., 2015). Furthermore, as presented in Table 1, some people may not use these devices continuously or even give up after a short period of trials. Prompting self-monitoring of behavior to users are suggested to maintain the continued walking behavioral change attributable to WFTs and SPAs (Bird et al., 2013), and eventually cultivate a healthy lifestyle for individuals in a longer term (Asimakopoulos et al., 2017). Last but not least, providing some incentives to encourage walking are also recommended. There are numerous smartphone apps (e.g., Sweatcoin and Carrot Rewards) allowing their users to redeem walking steps for cash vouchers and even donations to charities. Some of them are financed by the local government and only applicable to their residents. The Hong Kong government and non-governmental organizations may consider launching a similar walking-step-award redemption app to provide incentives and promote walking.

Aside from encouraging the use of WFTs and SPAs, the presence of a supportive environment considerably contributes to promoting walking (for both transportation walking and recreation/leisure walking) (Lu et al., 2017; 2019). The Hong Kong government announced the “Walk in Hong Kong” initiative in the Policy Address 2017 and has been formulating the planning and design standards of a pedestrian-friendly and walkable environment to the local people and inbound tourists for fostering walking behavior. Providing safe, comfortable, connected, and continuous walking facilities are paramount, urgent, and necessary (Wang et al., 2013). Walking environment is one of the key factors affecting the decision of walking as presented in Table 2. Widening the narrow walkways to enhance the walkability for pedestrians is recommended. Although it may not be feasible to apply it to the congested urban areas with limited road space (e.g., Central Business Districts), the improvement scheme could be strategically placed at selected locations in highly populated residential areas, and near schools and elderly community centers where the residents and users consider walking as their primary mean of transport. The provision of more pedestrian-friendly walking maps and directional signages along footpaths are also recommended.

Some traffic calming measures can be considered, which include the following: (1) implementing pedestrianization schemes to restrict vehicular access and reserve the space for walking during off-peak hours, weekends, public holidays, special events, and festivals (Szeto et al., 2016). The areas with open markets, where are often overwhelmed by stalls, wooden carts, and crowds, are particularly applicable. It also improves the comfort of walking and road safety by limiting the conflicts between pedestrian and vehicular movements; and (2) introducing low-speed limit zones to improve the walkability in the area with many street activities. It offers a similar outcome as the pedestrianization scheme (Li et al., 2019) but causes fewer disturbances to the local traffic.

6. Conclusion

With the potential to relieve numerous urban transportation problems, walking has drawn substantial scholarly attention in recent years, due in part to its health, environmental, economic, and social benefits to individuals and the society. Promoting walking has been frequently witnessed virtually everywhere all over the world. In addition, the contributions of WFTs and SPAs to motivating walking have been confirmed in a range of recent research. However, existing literature has rarely examined the transport mode change attributed to the use of these devices.

In light of this, a stated-preference questionnaire survey was conducted to collect 2,020 observations from 505 respondents in Hong Kong, an example of a transit-oriented city, about their transport mode choice. A series of binary logit models were developed to depict the significant factors influencing people's transport mode choice. Market segmentation analysis was conducted to examine the variations in travel decisions of users and non-users of WFTs and SPAs in short and long trips. The results show that the users of WFTs had a preference for a transport mode with more walking steps than the non-users. A possible explanation is that the users have already developed their habit of achieving the daily target of walking steps. It matches with the observation that more than 40% of the respondents strongly agreed that these devices can provide them an incentive to walk more. Moreover, the model findings reflect that people generally preferred traveling by public transport and getting off at a station earlier followed by walking for a partial trip, and they tended to walk faster (with a shorter walking time) for more walking steps. The results of market segmentation analysis and model validation show that the sub-models for short and long trips are significantly different, and both informative and reasonable to explain the data variation.

Some transport policy measures are recommended in this study, which include (1) enhancing people's motivation of walking by organizing some events and campaigns to encourage the use of WFTs and SPAs and share their walking records with their friends in social media, prompting self-monitoring of behaviour to the users of these devices, and providing incentives to redeem walking steps for cash vouchers and even donations to charities, and (2) improving the walking environment by widening the narrow walkways at selected locations in highly populated residential areas, and near schools and elderly community centres where the residents and users consider walking as their primary mean of transport, providing more pedestrian-friendly walking maps and directional signages along footpaths, implementing pedestrianization schemes to restrict vehicular access during off-peak hours, weekends, public holidays, special events, and festivals, and introducing low speed limit zones to improve the walkability in the area with many street activities.

There are several limitations in this study and we suggest the following research directions for future study: (1) The effectiveness of the proposed measures (e.g., providing incentives by a walking-step-award redemption app) is uncertain, a follow-up stated preference survey incorporating these associated contributory factors (e.g., award redeemed from walking steps) is recommended. (2) Some people may not use WFTs and SPAs continuously, and hence their effects on transport mode choice in the long-term are doubtful. Hence, we suggest recruiting participants who had no experience of using WFTs and SPAs before for a one-year experiment to record their change of walking behavior and gain a broader picture of the association between usage of these devices and transport mode choice, and (3) Walking environment is one of the key factors affecting the decision of walking. However, there is no empirical evidence to identify the quality aspects of the walking environment most in need of improvement from the perspective of pedestrians. A comprehensive study to prioritize the improvement areas on the walking environment is therefore suggested.

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