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Willingness-to-Comply Analysis of Incentive Mechanisms for Alleviating Local Congestion in Metro Waiting Areas

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ABSTRACT

Effectively equilibrating passenger distribution on metro platforms and carriages is important for relieving local congestion. This paper explores the role of incentive mechanisms in encouraging passenger queuing behaviours. To quantitatively analyse passenger compliance with the policy, a questionnaire survey was conducted in Fuzhou, China. According to the preliminary analysis of the survey data, passengers have various moving distance preferences under the incentive scenarios, namely, no movement, smaller distance and greater distance. Additionally, this paper establishes a nested logit model that considers travel purposes and moving distances. The empirical results show that although monetary and point-system incentives can effectively enhance passenger compliance with transfer queue-positioning requirements, when the moving distance is very small, people pay less attention to rewards. Compared to those commuting on weekends, passengers commuting on weekdays comply with policies more strongly, and the effect of implementing incentive policies is better; however, the effect of those policies is reduced among those travelling for leisure. Meanwhile, when travelling for leisure, as the number of companions increases, people's willingness to follow guidance on where to wait increases. According to the results, the implementation of incentive-based waiting encouragement policies during peak working days can result in good compliance.

KEYWORDS

compliance; local congestion; incentive mechanism; nested logit; waiting area.

1. INTRODUCTION

As population sizes increase, increased urban traffic congestion is reflected not only in road traffic but also in certain public transportation stations. Metros play an important role in public transportation due to their large capacities, low pollution and high speed. This transportation type shows great promise for medium and large cities in countries with large populations [1]. In particular, millions of passengers rely on metro systems for their daily commutes [2]. From this perspective, it is very important to improve the service level of metros [3]. Taking passenger boarding and alighting as an example, if the relevant facilities of the metro platform can be reasonably arranged, the operational efficiency of the metro company and passenger satisfaction can be improved to a certain extent. An obvious characteristic of subway stations is the variation in passenger flows across stations, and central stations are often congested, which affects the efficiency of passenger boarding and alighting [4]. Therefore, to improve the waiting environment, it is necessary to relieve local crowding pressure in metro areas and organise passenger waiting more appropriately.

The local crowding phenomenon is determined by not only the platform layout but also the distribution of waiting passengers [5]. Most previous studies have focused on optimising the layout of platform facilities to reduce the crowding degree of people waiting on platforms [6]. However, evacuation methods or measures to explore congestion in waiting areas have rarely been explored from the perspective of individual subjective willingness. According to our previous research, the waiting distribution of passengers is related to the location of infrastructure such as escalators [7]. Some scholars think that passenger platform choice is affected by the entrance location [8]. For example, Krstanoski noted that metro passengers can be divided into 2 types based on their waiting behaviours: those who prefer to board at the platform exit and those who prefer to board in an uncrowded area [9]. This division leads to the phenomenon that local congestion in metros is highly related to station exits and entrances [10].

On the other hand, frequent local congestion in the waiting area may also be transmitted to the carriage interior. Specifically, passengers already on a metro carriage are less likely to move between two adjacent carriages, and the number of people getting on the train directly affects the passenger flow density of the corresponding compartment. This situation means that the same factors that influence the boarding passengers' distribution influence the distribution of alighting passengers and the time consumption of passenger boarding and alighting [7, 11].

Fortunately, the rapid development of smartphones is a good prerequisite for the implementation of some policies, as passengers can conveniently obtain information through smartphones. We can use smartphones to inform travellers of passenger traffic density on the platform and use some incentives to encourage people to choose reasonable waiting areas [7]. In fact, incentive policies have been widely used in transportation research and have had good results. Ettema et al. [12] tested the effect of using positive incentives on travel behaviour on a congested highway in the Netherlands. Commuters received money or points to avoid congestion during the morning peak. Volinski [13] found that the economic strategy of implementing fare discounts increased passenger capacity between 13% and 86%. Gao et al. [14] found that both positive and negative incentives effectively alleviated the illegal parking of shared bicycles in cities. Obviously, the effectiveness of using incentive strategies to improve individual behavioural decision-making has been studied and verified by some predecessors.

However, the effects of incentives vary in guiding passenger flow in metro waiting areas. Keemin Sohn [15] claims that setting up electronic display screens along the platform to provide travel information is an effective way of adjusting the distribution of passengers on the platform. This method relies on passengers' abilities to self-organise and independently adjust to problems encountered in the travel process [16]. This ability can even cause travel efficiency to exceed the optimal value [17]. However, Van et al. claim that the application of self-organisation capabilities has certain limitations, although it can improve the flexibility and robustness of the system [18]. That is, at the level of measure implementation, plenty of room remains for exploration and research on how to develop a reasonable incentive and its intensity to ensure people's compliance.

This paper explores the movement behaviours of passengers and determines how incentive mechanisms affect behavioural changes when passengers move a certain distance. The rest of this paper is structured as follows: in the next section, the implementation process of the entire incentive strategy is described, and a theoretical model framework is constructed. The third part introduces not only the data collection process of this study – including the background of the surveyed city, questionnaire design and survey method – but also the construction process of the nested logit (NL) model. The fourth part introduces the research results and explores the main factors affecting passenger compliance behaviour and the differences and similarities in the implementation of the two incentive methods. The final section concludes the study by presenting the findings and discussing recommendations for future research.

2. THE THEORETICAL MODEL

Incentive methods affect passengers' travel decision-making to some extent. This paper considers some external factors and uses the theory of planned behaviour to reflect the passenger decision-making process after adding incentive methods.

2.1 Incentive process description

According to previous research [12, 13], financial incentives influence passengers' behavioural decisions when travelling. Since passengers have different choice preferences [14], this paper designs the implementation process of economic incentives (including monetary and point-system incentives) to better study the implementation effect of the various incentive methods.

The metro's installed sensor-recognition systems were set to detect congestion in carriages and waiting areas. The collected passenger flow information, the walking routes and the rewards in the designated areas were processed and summarised. Passengers who meet the incentive implementation conditions receive an incentive message. Once a passenger reaches the designated carriage, he or she is recognised as having completed the task and receives a reward. The overall process of the incentive strategy implementation is shown in *Figure 1*.

Our incentive strategies are not implemented under all circumstances; certain limited conditions need to be met before the incentives are implemented, such as reaching a certain passenger flow. At the same time, our strategy needs to be implemented based on ensuring the safety of passenger boarding and alighting.

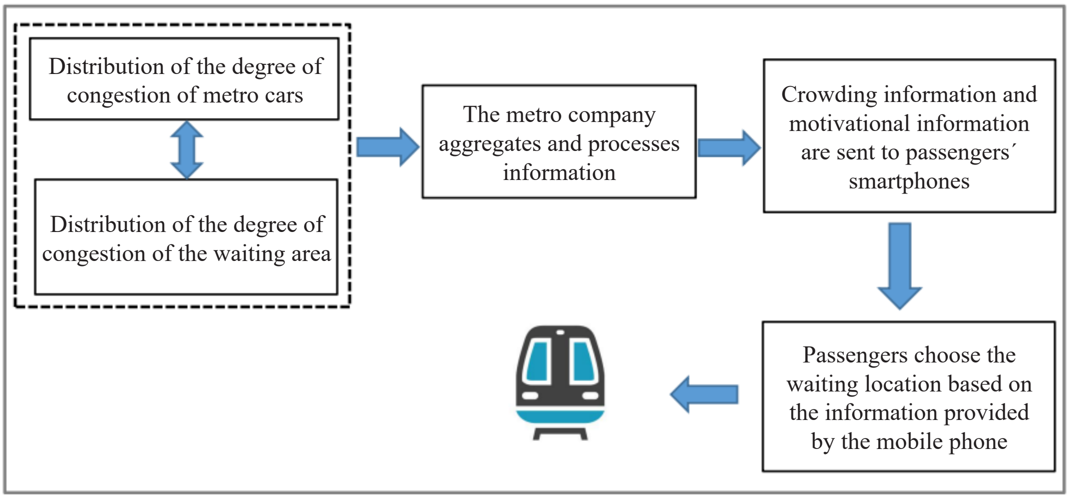

Figure 1 – Incentive strategy implementation process

2.2 Theoretical model framework

We use the theory of planned behaviour (TPB) model to describe the decision-making process of passengers waiting in metro systems under our incentive methods. In theory, we consider the waiting environment, the moving distance and the value of rewards as external factors that influence people's mobility choice behaviours. Specifically, the concept of the TPB theory is defined here as "perceived behavioural control" and is defined as an individual's perception of his or her ability to violate or comply with policies. "Attitudes" reflect the user's degree of dependence on metro and consumption costs, and the variable indirectly measures the degree of policy compliance. "Subjective norms" refer to the social pressure caused by users who are unwilling to participate in incentives and who queue based on their wishes. "Policy intervention" refers to administrative measures that encourage passengers to move to the designated place via various incentives. The theoretical model framework of policy compliance in this study is shown in *Figure 2*. The willingness to comply with policies is situated at the innermost part of the model. "Policy intervention" is used to obtain the evolution of people's behaviours through this constructed environment, and the setting of these TPB-based questionnaire items is illustrated in the subsequent sections.

3. DATA SURVEY AND MODELLING

Our data collection time was concentrated on workdays and weekends from 1 August 2021 to 30 September 2021, in Fuzhou. The directions of the two metro lines and the administrative area around the lines are shown in *Figure 3*. The data were collected through on-board surveys, which were chosen mainly because each questionnaire was over 10 minutes long. If a different survey method were chosen, passengers who were tight on time might have abandoned the survey. Currently, passengers often face two or more choices during the travel process, so the travel purpose and the moving distance are discrete. Due to the complex relationship between travellers' mobility behaviours and motivation levels, travel decisions usually have a complex hierarchical structure.

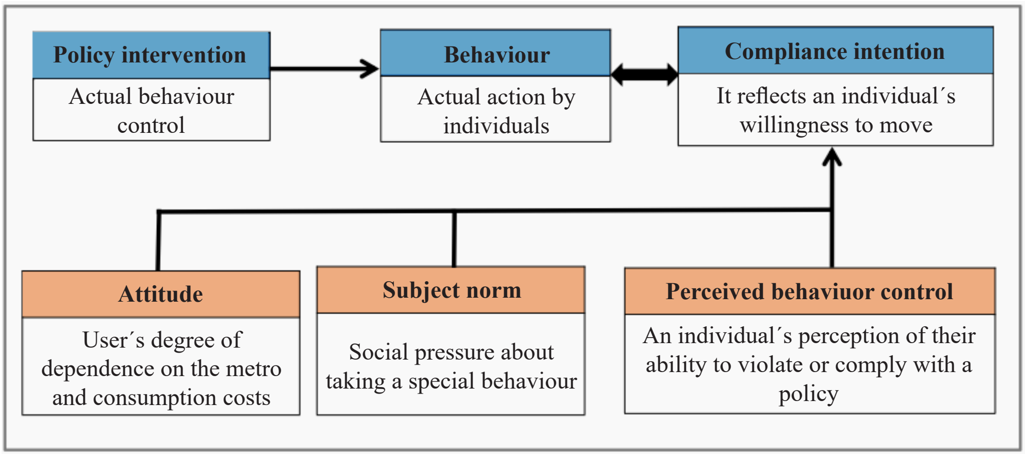

Figure 2 – Theoretical model framework for policy compliance

Figure 3 – Map of Fuzhou metro lines 1 and 2

3.1 Data survey

Based on previous research [19], when respondents agree to reveal their preferences and complete preference surveys in familiar environments, their answers are closer to reality. *Figure 4* briefly describes our investigation process. The first step was to invite the respondents to participate in the survey and introduce the questionnaire. In the second step, the surveyor randomly selected one of the four prepared pictures of the waiting environment

What would you do if there were incentives?

In this section, we'd like to know your attitude towards incentive policies. Under the incentive policy, you will have a more comfortable queuing environment and faster boarding speed. Our purpose is to let you imagine how you will behave after the implementation of incentive policies in the future. The following are the implementation steps of the questionnaire:

Step one: Introduce the background and purpose of this survey. It is worth noting that we should avoid making respondents aware that their behaviors were inappropriate.

Step two: Stated preference pivot with controlled conditions. e.g.: "Now suppose someone gives you a **2-yuan** monetary reward **2 minutes** before the metro arrives and asks you to move to other areas to line up. How far would you be prepared to move?"; "How far would you be prepared to move if someone gives you a **20 point** reward **1 minute** before the metro arrives "

Step three: Record the personal characteristics and trip characteristics of the respondents. The answers were mainly completed by the investigators while chatting with the respondents.

Step four: Meteorological information supplement. The logged information about the weather included temperature, humidity, wind speed and visibility.

The amount of incentive intensity and time (in shadow) among these three questions was maintained in a progressive relationship, and variable levels of change were given to different respondents. Each respondent only needs to answer the three questions corresponding to one of the monetary reward or the point system reward.

Figure 4 – Example of the survey process (questions translated from Chinese)

(as shown in *Table 1*) and asked the respondents if they would like to wait for trains in such an environment. At the same time, considering that the reminder time of incentive information is an important factor affecting passenger movement behaviours, this survey sets three time intervals for releasing incentive information, which represent the time between the release of information and the arrival of vehicles: 1~2 minutes, 3~4 minutes and more than 4 minutes. The reward types include red envelope rewards and point rewards; the red envelope reward intensity fluctuates between 1 yuan and 10 yuan, and the point system incentive fluctuates between 1 yuan and 100 yuan. The surveyor randomly changed the incentive release time and reward value three times to obtain the travel distances of passengers. In the third step, we surveyed the passengers' personal characteristics (gender, age, education, job etc.) and trip characteristics (fare, distance etc.) to determine basic information about their travels.

Table 1 – Four waiting environment levels

Scenes				
Number of columns	2	3	5	3
Number of rows	3	3	5	4
Per capita floor space [m²]	0.73	0.51	0.36	0.32

Based on the questionnaire content, each respondent was asked about the maximum acceptable moving distance under the incentive levels. To better observe the users' response to certain incentives, we introduced the "marginal reward rate" as the ratio of the incentive to the maximum moving distance. The marginal reward rate is the ratio of the additional reward for performing an additional action to the cost of that action. We define it as the ratio of the incentive to the maximum distance moved, and the greater the marginal reward rate, the greater the monetary reward to persons who move further. For example, if the monetary reward value was 1 yuan (approximately 0.15 US dollars), 5 yuan (approximately 0.79 US dollars) and 10 yuan (approximately 1.58 US dollars), the acceptable maximum moving distances for a surveyed user were 0.5 m, 10 m and 15 m, respectively. Thus, the "marginal reward rate" under the monetary incentive was 2 yuan per m, 0.5 yuan per m and 0.67 yuan per m. Larger marginal reward rates mean that people who move greater distances receive more money. In the follow-up study, we chose the maximum marginal reward rate to explore passenger movement. This method can be used to measure the relationship between the incentive and the maximum travel distance more effectively and to better observe users' responses to incentives. The scatter plot of the relationships among the reward values and the moving distances is shown in *Figure 5*.

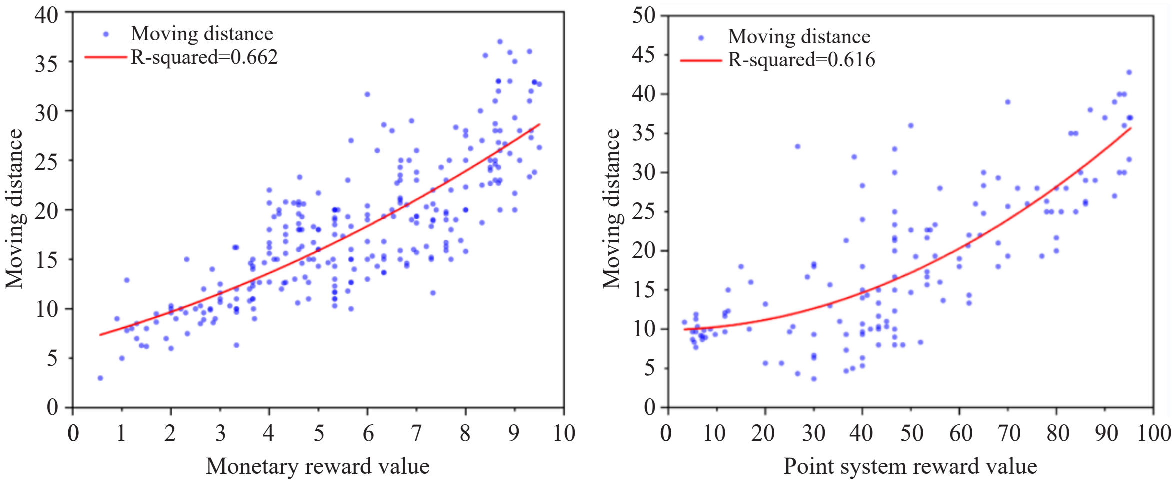

Figure 5 – Scatter plot of the relationship between the incentive intensity and the reward

The general trend of the above figure indicates that, regardless of whether the incentive was monetary or a point system, larger incentive values translate to the passengers' inclination towards a greater distance. When the incentive value was small, the two incentives resulted in the passenger's moving distance concentrated at approximately 10 m. When the incentive value increased, the monetary incentives were more concentrated than the point-system incentives for the passengers, which was mainly due to the passengers' incentive preferences. When the incentive value was further increased, the passengers moved farther under the point-system reward.

A total of 418 valid questionnaires were obtained. Initially, we conducted face-to-face surveys with 470 metro passengers. After this survey, we excluded 52 passengers who did not complete the survey or who responded to the questionnaire in an unclear manner.

The sample distribution is shown in *Table 2*. Notably, working passengers accounted for 95.2% of the respondents, so a large proportion of the users used the metro for commuting purposes. In terms of educational level, 78.5% of the respondents had a college degree or above. Regarding payment methods, 93.8% of the passengers used smartphones or metro cards. Passengers who used these two payment methods generally travelled more frequently than other passengers, which provides a good way of implementing the proposed policies [7]. Therefore, the statistical results showed that the subjects of our study had a high educational background, and the payment methods reflected the current reality of the popular use of smartphones and identity cards in China.

Table 2 – Demographics and usage characteristics of the survey sample

Gender (%)		**Date (%)**	
Male	56.0	Weekday	62.7
Female	44.0	Weekend	37.3
Age (%)		**Baggage weight (%)**	
<18	20.2	0–1 kg	54.3
18–30	44.6	1–3 kg	33.7
31–40	21.9	3–6 kg	7.7
>40	13.3	>6 kg	4.3
Employment status (%)		**Payment method (%)**	
Employee	95.2	Smartphone or metro card	93.8
Not an employee	4.8	Other	6.2
Education (%)		**Travel purpose (%)**	
High school or lower	21.5	Commuting or going to school	34.3
Bachelor's degree	67.7	Leisure or going home	45.6
Graduate degree	10.8	Affairs	20.1

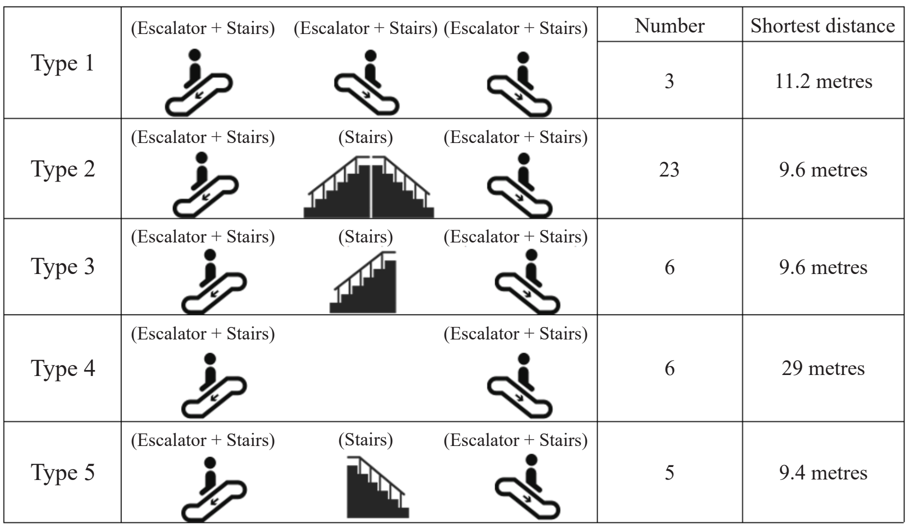

Figure 6 – Infrastructure types and distances in the waiting areas of the two metro lines

In addition, the infrastructure distribution was investigated, mainly because the layout of the facilities in the waiting area affects people's walking routes on the platform [20]. Fuzhou has two elevation types: escalators and box elevators. The latter occupy a relatively small area and are not considered in this paper. The distribution of escalators and stairs at all stations on Lines 1 and 2 (except the first and last stations) was investigated. According to the survey results on the distance between facilities, the Fuzhou metro waiting area can be divided into 5 types. The number of each station type and the minimum distance between the two facilities are shown in *Figure 6*. In Fuzhou, 53.5% of the stations are Type 2, in which the minimum distance between infrastructures is 9.6 m.

3.2 NL model construction

Our paper primarily explores the main factors that influence the willingness of passengers to move in metro waiting areas from the perspective of economic incentives. In the discrete choice analysis, which is an appropriate basis for the willingness-to-move analysis, decision makers are modelled as selecting alternatives from choice sets based on the highest utility [21]. Logit models are often used to represent nonlinear functional relationships between the probabilities of alternatives and the variables that influence behavioural decisions. The multinomial logit (MNL) and NL models are two commonly used models in the field of discrete choice analysis [22, 23]. However, the MNL model has certain property limitations, such as the alternative being an independence of irrelevant alternatives (IIA). Passengers usually choose to travel according to their own preferences, so it can be predicted that the IIA attribute is not satisfied. Therefore, this paper chooses the NL model to analyse passenger movement behaviour under the incentive strategy.

Based on the correlation analysis of the model variables, we found that the passenger travel distance varied greatly across travel purposes (commuting and leisure). In this paper, two reward forms (point-system and monetary incentives) were involved and available to observe the variable correlations, as shown in *Figure 7*. Interestingly, the most significant result was that commuters tended to choose to move large distances under different incentives, different from the behaviours of leisure travellers, and the mobility choices of passengers in the two scenarios were different when the incentive value was low. Therefore, we included the travel purpose in the upper layer of the NL model to analyse the movement behaviours of metro passengers. The structure of the NL model in the paper is shown in *Figure 8*. We assume that the compliance intention of moving is divided into 3 levels, including O (not moving), A (moving distance within 10 metres), and B (moving distance greater than 10 metres). Since passengers have great differences in their intentions depending on whether they are commuting or travelling for entertainment, the purpose of travel is used as the upper model, and the travel distance is used as the lower model.

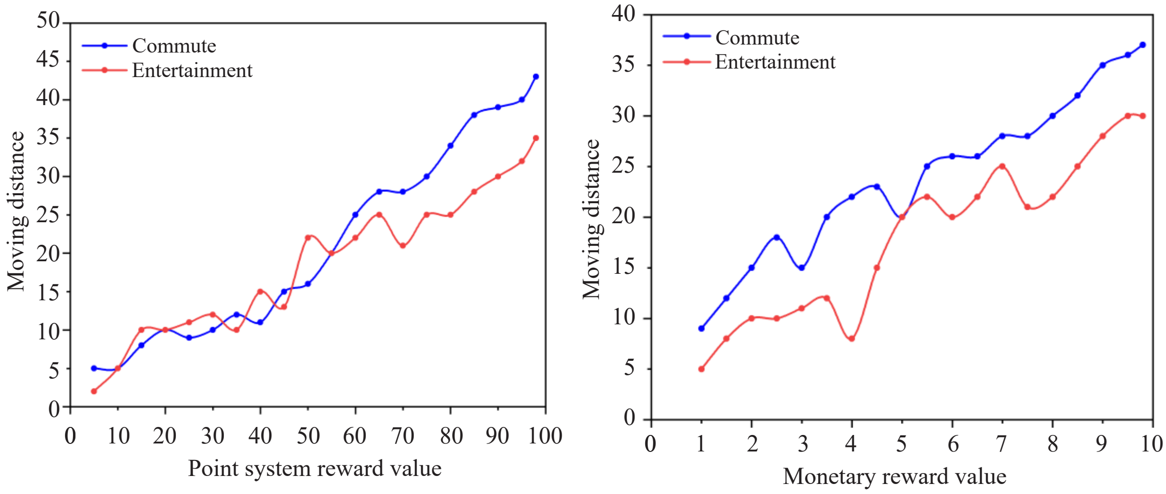

Figure 7 – Variations in passenger travel distance for the incentives across travel purposes

The travel destination and moving distance choice process of a passenger can be described by a utility function. The utility function is divided into two parts, as shown in *Equation 1*. The first component is the observed utility of the alternative, and the second component is a random term that depicts the effects of unobserved characteristics on the utility:

$$U_{in} = V_{in} + \varepsilon_{in} \tag{1}$$

$$V_{in} = V_{(r|m)n} + V_{mn} \tag{2}$$

where U_{in} represents the total utility of passenger n; V_{in} represents the total utility of the passenger selection scheme; and ε_{in} is the random interference term of passenger n. V_{in} describes the utility decomposition form when passengers choose a solution. $V_{(r|m)n}$ is the fixed term formed when passenger n chooses option r; V_{mn} selects a solution for passenger n to follow the utility changes of the fixed project at destination m. Formulas can be used to calculate the utility differences of passengers across schemes and destinations. $V_{(r|m)n}$ is a fixed term that is independent of the destination and may depend on passengers' own preferences, habits or other factors. V_{mn} represents the change in utility generated by passengers when choosing a solution based on changes in destination.

If the passenger's utility fixed term is linear, then the expressions $V_{(r|m)n}$ and V_{mn} are shown in *Equations 3 and 4*, respectively.

$$V_{(r|m)n} = \sum_{k=1}^{K_1} \beta_k X_{(r|m)nk} \tag{3}$$

$$V_{mn} = \sum_{k=1}^{K_2} \theta_k X_{mnk} \tag{4}$$

where $X_{(r|m)nk}$ is the k^{th} characteristic variable in the lower-level model selected by passenger n, and it responds to changes in r; X_{mnk} is the k^{th} characteristic variable in the upper-level model selected by passenger n; β_k is the coefficient of $X_{(r|m)nk}$; and $\theta_k (k=1,2,...K_2)$ is the coefficient of X_{mnk}.

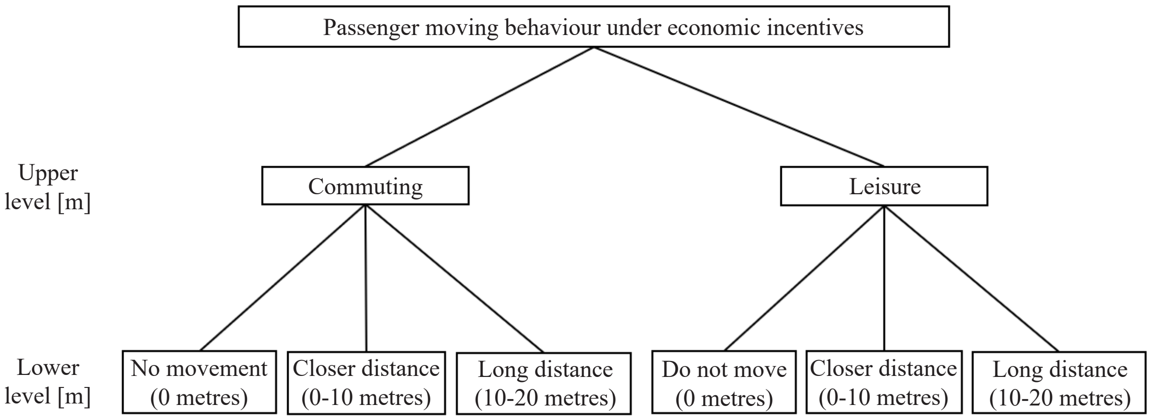

Figure 8 – The NL model structure

Table 3 shows the main observed variables of the NL model. We select variables using a backwards culling method, which considers all variables to be included in the model and measures the contribution of the variable to the model. It can remove the least important variables early on, leaving only a few important variables in the model. We divide and explain the variables according to behavioural attitudes, perceived behavioural control, government intervention and subjective norms. Factors in the questionnaire include queuing scene, occupation, housing area etc. Due to their representation in the model, we do not explain them further in this table. We use NLogit 6.0 software to estimate the model.

4. MODEL RESULTS

We used NLOGIT 5 software to estimate the model. *Tables 4 and 5* show the estimated results and t-test values. According to the results of the model, the t-test absolute values of 81.5% of the model variables were greater than 1.65, which indicates that these variables had significant impacts at a 90% confidence level on passengers' decision-making behaviours under the economic incentive strategy.

The traditional R^2 assumes that the regression model is linear, while the logit model we chose to analyse is nonlinear. In the nonlinear model, the traditional R^2 may not capture the accuracy of the model fitting effect, so the pseudo-R^2 is chosen in this paper to measure the degree of the model's sum. However, there is

Table 3 – Descriptive statistics of observable variables

Category	Variable name	Description
Behavioural attitude	Tolerance	Maximum number of people in line that respondents can tolerate.
	Reminder time	Reminding respondents to move before the metro arrives.
	Frequency	The number of times the respondents got on or off at the wrong subway station each month.
	Baggage weight	The weight of baggage carried by respondents.
	Number of bags	The number of bags carried by the respondent.
Perceived behaviour control	Companions	The number of peers with the respondents when they move.
	Elasticity	The ratio of the distance travelled by the respondent to the incentive amount.
Policy intervention	Monetary incentive	The amount of monetary incentive.
	Point reward	The amount of points system incentive.
Subjective Norm	Trips	The number of times the respondent uses the metro per week.
	Job	Respondent's occupation.
	Day	The day of the survey. The value is 1 for working days and 0 otherwise.
	Area	The respondent's housing area.
	House	The number of homes owned by respondents.
	Phone	The amount of time respondents use their mobile phones each day.
	Gender	The gender of the respondent. The value is 1 if the respondent is female; otherwise, it is 0.
	Age	Age of respondents.
	Culture	The education level of the respondents.

also a direct mapping between the two. The pseudo-R^2 value of the NL model is 0.3, the corresponding R^2 value is approximately 0.7, the pseudo-R^2 value of the MNL model is 0.28, and the corresponding R^2 value is approximately 0.5 [24]. This indicates that the NL model has high accuracy and can be used to describe the decision-making behaviours of passengers under incentive strategies. $L(0)$ represents the value of the likelihood function of the zero model, and a smaller value means that the model does not explain the data well. $L(\hat{\theta})$ represents the likelihood function value of a multinomial logit model fitted using the maximum likelihood method. It is used to evaluate how well the model fits the observed data after fitting. The larger the value of $L(\hat{\theta})$, the better the fitting effect. Therefore, the following section mainly analyses passenger behaviour through the output results of the NL model.

From the perspective of the performance of the explanatory variables, in the two scenarios of commuting and leisure, the monetary and point-system incentive methods had both similarities and differences in terms of encouraging passenger movement. In terms of their similarities, regardless of whether monetary or point-system incentives were used when the moving distance exceeded 10 m, the incentive was greater, and the passengers tended to move greater distances. In contrast, when the moving distance was within 10 m, the effects of the two incentives were not significant. The overall situation of the model parameter fitting showed that the main factors affecting passenger movement within 10 m were nonmotivating, such as housing and baggage weight. When the moving distance exceeded 10 m, monetary and point-system incentives started to become significant. This result was consistent with the information we obtained in the actual survey. When the moving distance increased, the passengers considered whether to follow the guidance based on the reward values. Notably, the research conclusions of Ettema et al. [12] are basically consistent with our expectations. In the

Table 4 – Parameter evaluation of the MNL model

Model	Variable name	Coefficient	t stat
Commute	Tolerance (A)	-0.07***	-3.40
	Gender (A)	0.62***	3.98
	House (A)	-0.94***	-4.25
	Phone (A)	0.13***	3.73
	Companions (A)	0.01	0.09
	Number of bags (A)	-0.50***	-2.97
	Monetary incentive (B)	0.40***	4.80
	Elasticity (B)	2.99***	15.97
	Point reward (B)	0.18***	14.05
	Trips (B)	0.054***	2.88
	Job (B)	0.14	.43
	Day (B)	0.36**	2.30
	B	-8.72***	-10.08
Entertainment	Phone (A)	0.09**	2.46
	Trips (A)	-0.09***	-4.14
	Baggage weight (A)	-0.27***	-3.24
	Companions (A)	0.32**	2.48
	House (A)	-0.73***	-3.31
	Area (A)	-0.40	-0.67
	Point reward (B)	0.17***	12.53
	Reminder time (B)	-0.07	-0.99
	Monetary incentive (B)	0.35***	4.02
	Frequency (B)	-0.19	-1.01
	Elasticity (B)	2.95***	15.59
	Number of bags (B)	-0.33**	-2.42
	A	1.57***	3.01
	B	-7.64***	-9.24
	$L(0) = -517.4285$; $L(\hat{\theta}) = -413.7607$; pseudo-$R^2 = 0.2811$		
Upper level	Reminder time	0.44***	4.37
	Frequency	-0.50***	-2.82
	Age	0.05	0.61
	Trips	-0.08	-0.95
	Number of bags	-0.75**	-2.04
	Phone	0.09**	2.45
	Tolerance	-0.03*	-1.93
	Job	0.71	1.45
	Culture	-1.05***	-4.75
	Companions	0.07	0.49
	$L(0) = -326.4453$; $L(\hat{\theta}) = -314.6407$; pseudo-$R^2 = 0.2571$		

*ASC means alternative specific constant; *p value < 0.1; **p value < 0.05; ***p value <0.01.*

Table 5 – Parameter evaluation of the NL model

Model	Variable name	Coefficient	t stat
Commute	Tolerance (A)	-0.07**	-2.43
	Gender (A)	0.41**	1.91
	House (A)	-0.83***	-3.60
	Phone (A)	0.11***	3.04
	Companions (A)	0.02	0.11
	Number of bags (A)	-0.25	-1.25
	Monetary incentive (B)	0.39***	4.83
	Elasticity (B)	2.78***	7.93
	Point reward (B)	0.17***	8.06
	Trips (B)	0.06***	2.81
	Job (B)	0.26	0.79
	Day (B)	0.34**	1.90
	B	-8.85***	-7.80
Entertainment	Phone (A)	0.14***	4.17
	Trips (A)	-0.09***	-3.45
	Baggage weight (A)	-0.3**	-2.01
	Companions (A)	0.26**	2.03
	House (A)	-0.81***	-3.88
	Area (A)	-0.49	-1.22
	Point reward (B)	0.17***	9.97
	Remind time (B)	0.17**	2.19
	Monetary incentive (B)	0.40***	4.35
	Frequency (B)	-0.43**	-2.47
	Elasticity (B)	2.94***	12.1
	Number of bags (B)	-0.56**	-1.93
	A	1.09*	1.84
	B	-8.48***	-8.24
	$L(0)$ = -528.1971; $L(\hat{\theta})$ = -401.1557; pseudo-R^2 = 0.3077		
Upper level	Reminder time	0.14***	2.89
	Frequency	-0.22*	-1.89
	Age	0.02	0.32
	Trips	0.07***	4.29
	Number of bags	0.11	1.19
	Phone	0.04*	1.74
	Tolerance	0.02	1.49
	Job	0.77***	3.71
	Culture	-0.94***	-4.5
	Companions	0.15*	1.8
	$L(0)$ = -357.1447; $L(\hat{\theta})$ = -321.4231; pseudo-R^2 = 0.2653		

absence of continuous incentives, the inability of the behaviour shown in the experiment to be sustained does not affect our expectations for the strategy. Those who are motivated by our mechanism and have moveable time can move and earn rewards. However, when approaching pick-up and drop-off times, from a safety perspective, our mechanism also no longer encourages people to move to obtain a reward, as this behaviour poses a security risk. The coefficients of monetary and point-based rewards for commuting were different. The coefficient for monetary rewards was 0.39, while that for point-based rewards was 0.17. This means that the odds ratio (OR) values for the user's movement in the commuting state were 1.47 and 1.19 times greater than the user's unwillingness to move when all other conditions remained the same (PA/PO and PB/PO, respectively). This analysis shows that the monetary and point-system reward coefficients were relatively close for the two trip types. However, the monetary incentive coefficient was always greater than the point-system incentive coefficient, which shows that under these two types of incentives, monetary incentives can often cause passengers to move further. When these results were combined with the preliminary data analysis, when the two reward types resulted in a reward with the same numerical value, most passengers chose the monetary reward without hesitation, based on experience. However, when the numerical values differed and the monetary values were the same but were presented in different forms, users had different preferences.

From a personal attitude perspective, baggage weight and the number of bags played the same role in travel, indicating people's negative feelings about the policies when carrying baggage. In both scenarios, regardless of whether users moved short or long distances, the two factors had a negative impact on policy compliance. Notably, these two factors had varying degrees of influence on commuting and leisure. Compared to commuting, passengers are less comfortable carrying baggage during leisure time. The other two variables that reflected the relationship between personal attitudes and willingness to comply were tolerance and release time of incentive information. In the model, the former had a negative effect; that is, passengers with greater tolerance exhibited worse policy compliance. The main reason for this may be that passengers with a high degree of tolerance can accept more crowded waiting environments and are more likely than those with a low degree of tolerance to choose not to change their waiting positions when incentives are implemented. When travelling for leisure, the release time of incentive information was significant for moving more than 10 m and was positively correlated with the distance travelled, indicating that passengers require more time to move greater distances. Specifically, more time elapsed between the moment the information was released and the arrival of the metro. The 'frequency' variable is also important, as frequent trips to the wrong subway can have a negative impact on policy compliance. To reduce the frequency of errors, passengers may not be willing to change their waiting positions.

The gender variable was significant under commuting conditions, and the OR value of women was 1.5 times that of men. This result shows that under commuting conditions, women were more willing than men to move by up to 10 m because in Asia, especially in China, women are more willing to engage in beneficial tasks. Thus, they are more sensitive to rewards [25, 26]. The housing variable was used here to measure user income level because we consider that subjective bias may be large in the monthly income of the passengers who were directly surveyed, and the number of houses may reflect personal economic conditions. Based on the performance of the model variables, we found that "housing" was similar in the two scenarios, which was consistent with our estimation. That is, passengers with higher economic power were less willing to move and less willing to follow the policy guidance, but the negative impact was less significant than it was in the commute trip scenario. The trip variable effectively indicated the passenger's familiarity with the metro. More trips per week indicated a stronger dependence on the metro. Those who relied more on the metro tended to abide by the policy guidance in the commuting scenario. In the leisure trip scenario, the passengers pursued free and convenient travel, which also reflects that people want more autonomy and are thus reluctant to queue in accordance with policy requirements. From the perspective of utility theory, metro waiting resources in the commuting environment are limited, and personal needs cannot be met. Passengers must compensate for this lack of personal resources by participating in various activities when pursuing entertainment. If these resources cannot be compensated for, people feel a sense of loss, which affects their normal activities [27]. The date variable represents the date on which the questionnaire was completed. Compared with those travelling on weekends, users travelling on weekdays were willing to move farther. From the perspective of the travel chain, the main reason for this phenomenon may be that travel on weekends is easier to link with leisure travel at the time node. Therefore, their willingness to comply with guidance policies is reduced. From another perspective, people's emotional states during travel are contagious, spreading to the people around them. This phenomenon is reflected in the passengers who commuted on weekends clearly feeling a pleasant atmosphere around them, which produced an effect similar to that of travelling for leisure.

The companion variable was not significant in the commuting condition but had a positive effect on users' policy compliance in the case of leisure travel. Regarding the performance of this effect, more companions led to a greater likelihood of movement. There are two reasons for this finding. First, the phenomenon of companionship is more common while travelling for leisure, more communication space is needed, and passengers are more willing to move towards less crowded areas when they are with companions. Second, when people travel in groups, the satisfaction of one companion often affects the experience of his or her companions. Overall, passengers had the strongest policy compliance when commuting on weekdays, and the implementation of incentive policies was better at this time.

5. CONCLUSIONS

As an increasing number of people use the metro to commute in China, the government and metro management have been considering how to improve the metro waiting environment. This paper focuses on the impact of two incentive types on traveller mobility behaviour. It also analyses the various internal and external factors that influence the relationship between incentive form, incentive intensity and policy compliance for this behaviour. Different from previous studies on the influence and significance of certain factors on the travel behaviours of passengers, such as travel time and route selection [8, 28], we focus on exploring the changes in the distance moved by passengers after being provided with incentive information. The survey data analysis revealed that the implementation of incentive strategies enhanced users' compliance with information guidance and effectively alleviated local congestion in the waiting area. In addition, an NL model was constructed to analyse the main factors that motivated people to comply with information guidance across incentive values.

Overall, policy interventions have an important impact on users' mobile behaviour intentions. As expected, greater incentives cause users to be more willing to move. However, the implementation effects of the two incentive modes have certain similarities and differences. Taking 10 m as the boundary for dividing the distance, we found that monetary incentives and integral incentives did not have a significant incentive effect at short distances, as non-incentive factors had the main effects on passenger short distance movement. However, if policy makers want to encourage people to walk long distances, incentive value is a key factor affecting passenger travel. In a real policy environment, if people are encouraged to wait in a specific waiting area when they enter the station, monetary incentives play a greater role than point incentives. When the incentive value is further increased, the advantages of point-system incentives begin to strengthen, and users tend to move longer distances. In addition, users' heterogeneous characteristics, such as subjective norms and attitudes, can all affect passenger policy compliance. Among them, travelling with peers during entertainment events results in a better response to the incentive strategy.

From an economic perspective, this study adopts an incentive mechanism to encourage passengers to move during peak hours, which is an attempt to motivate people to resist the inertia of waiting. In fact, the main reason for local congestion on the platform is the asymmetry of the waiting information. In a limited space, users can easily rely on waiting inertia. This situation is similar to the consumer market; to reduce risks and protect their own interests, when true and false are difficult to distinguish, consumers reduce their purchase amounts as much as possible, resulting in the coexistence of a demand gap and an oversupply [29]. In contrast, if targeted congestion information is issued to passengers through incentives, this local congestion can be avoided. This study helps explain the relationship between different factors and passenger mobility behaviours under the incentive strategy. Based on the differences in how the two incentive measures are implemented, policymakers can design effective economic incentive schemes. For example, on nonworking days, managers can encourage users by transmitting waiting information through electronic screens, and on working days, they can implement different incentives to encourage users to move consciously.

Although this paper discusses how metro passengers have certain degrees of policy compliance and how to effectively alleviate local congestion in waiting areas, some restrictions still require further study. For example, on the issue of policy implementation boundaries, we will continue to explore when policy implementation best alleviates local congestion in metro waiting areas and how to determine when policies should be implemented. We will explore the amount of time before metro arrival in which such policies should be implemented to effectively organise passenger movement. On the issue of incentive methods, we examine the similarities and differences between monetary and point-system incentives in the implementation process. For example, in which scenarios are the two incentives best implemented, and are there better incentives? We will also focus on how to integrate the new types of sensing equipment with incentive policies in metro waiting areas so that guidance policies can help passengers smoothly board and alight. In addition, this article did not cover how to combine information on the degree of congestion in the carriage with that of the waiting area to improve the passenger waiting experience, a topic that will be further discussed in subsequent studies.

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高良鹏，段晓凡，简文良，王雪，陈德旺

缓解地铁等候区局部拥堵的激励机制遵从意愿分析

摘要：
有效平衡地铁站台和车厢的乘客分布对于缓解局部拥堵非常重要。本文探讨了激励机制在鼓励乘客排队行为中的作用。为了定量分析乘客对该政策的遵从情况，在中国福州进行了问卷调查。根据调查数据的初步分析，在激励情景下乘客有各种移动距离上的偏好，即不移动、距离较小和距离较大。此外，本文还建立了一个考虑旅行目的和移动距离的嵌套Logit模型。实证结果表明，虽然货币和积分制度激励可以有效提高乘客对换乘队列定位要求的遵从程度，但当移动距离很小时，人们对奖励的关注度较低。与周末通勤的乘客相比，工作日通勤的乘客则会更遵守政策。

关键词：
遵从性；局部拥堵；激励机制；嵌套Logit模型；等候区