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Modelling time-of-travel preferences capturing correlations between departure times and activity durations

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ABSTRACT

Departure time choice models quantify the relative impacts of the factors affecting travellers' departure time selection and help design targeted peak-spreading policies. The departure time preference of travellers is traditionally captured using parameters associated with different alternatives along three aspects – outbound, return, and duration. In reality, departure time decisions for outbound and return legs, and the corresponding activity durations, are interrelated in most cases. However, none of the previous departure time choice models has explicitly investigated the impact of this potential correlation on model outputs. To address this gap in the existing literature, we proposed a model structure with a novel polynomial functional form of alternative specific constants (ASCs) that captures this correlation in a joint (outbound and return) departure time choice model. A revealed preference (RP) dataset from Dhaka, Bangladesh, was used to model the joint departure time preferences of the car commuters. The proposed model was then compared with a state-of-the-art model that uses a trigonometric formulation of the ASCs. Results indicate that the proposed formulation yields more behaviourally realistic outputs compared to the trigonometric model by explicitly capturing the correlation between departure time and duration. While the specific outputs are applicable to car commuters residing in Dhaka, Bangladesh, the framework can be applied to better predict departure times and improve the formulations of the peak spreading policies in other contexts as well.

1. Introduction

Traffic congestion in dense urban areas primarily stems from the concentration of travel demand over the peak hours. This adversely affects the quality of urban life in various ways, including reduced travel speeds, greater variability in travel times, increased uncertainty in arrival times, higher operating costs (fuel consumption), heightened levels of air and noise pollution, and decreased safety (Li and Hensher, 2012; Newbery, 2005; Thorhauge et al., 2016). This challenge is further exacerbated by urban population growth leading to increased travel demand, a heavy reliance on cars for mobility, and inefficient demand management strategies (Batur and Koç, 2017; Hensher and Puckett, 2007; Pucher et al., 2007). Addressing the ever-increasing demand and mitigating the negative impacts of congestion necessitates a multifaceted approach, considering both supply and demand sides. Simply expanding infrastructure is not a sustainable solution, as it often leads to induced traffic due to increased capacity (Noland and Lem, 2002; Thorhauge et al., 2020). As a result, urban planners worldwide are placing growing emphasis on demand-side strategies to shift

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transportation preferences (Geng et al., 2023; Guo et al., 2021). These strategies range from direct measures like congestion pricing (which can lead to changes in mode, departure time and destination (Börjesson and Kristoffersson, 2018; Li et al., 2018; Saleh and Farrell, 2005) to less restrictive ones like implementing flexible work hours (Munch and Proulhac, 2023; van der Loop et al., 2019), time-variant fares (Hightower et al., 2022) providing incentives to travel during off-peak hours and under-utilised routes (Pan et al., 2016), promoting mixed land use to alter activity locations and channel traffic away from the downtown, etc. (Cervero, 1991). As reported by Thorhauge et al. 2016 "*a number of studies have shown that people are more likely to change their departure time to reduce congestion rather than changing mode* (e.g. Hendrickson and Planke, 1984, Bianchi et al., 1998, Hess et al., 2007), *and are even less likely to change their work and residential location* (Goulias et al., 2013)". However, despite their effectiveness, the design of policies to shift departure time has received less attention compared to strategies targeting mode shift and route choice (Arellana et al., 2013; Azhdar and Nazemi, 2020; Hendrickson and Plank, 1984; Huan et al., 2021; Thorhauge et al., 2021; Zhou et al., 2020), particularly in cities from developing country (Zannat et al., 2022). This is often attributed to the challenges of quantifying the relative impacts of factors influencing travellers' temporal demand, primarily due to a lack of dependable data sources and the synergies among various activity-travel related choice dimensions (Graham et al., 2020).

Departure time choice models, mathematically or statistically formulated to define time-of-day choices as a function of trip and level of service attributes and socio-demographic characteristics, play a crucial role in determining the temporal distribution of urban transportation demand (Bhat and Steed, 2002; Habib, 2021). Researchers attempted to develop various departure time choice models influenced by Vickrey (1969). These models and their modelling frameworks vary based on their context of application. Some utilised continuous time choice models using hazard-based duration frameworks, like Bhat and Steed (2002) and Wang (1996). Others have adopted a discrete choice framework, dividing the continuous departure time variable into a finite set of discrete intervals and modelling utility as a function of level of service attributes, socio-demographic factors, and activity-related variables. (Anowar et al., 2019; Bwambale et al., 2019; Chaichannawatik et al., 2019; Ding et al., 2015; Golshani et al., 2019). Small (1982), McCafferty and Hall (1982) and Holyoak (2008) used multinomial logit (MNL) model to understand commuters' departure time choices. The MNL model has also been used to predict the time-of-day choice to explore the differences between the weekday and weekend or holiday travel patterns (Chaichannawatik et al., 2019; Yang et al., 2008). Approaches like nested logit (NL), cross-nested logit (CNL), continuous CNL, and mixed multinomial logit (MMNL) relaxed the independence of irrelevant alternatives (IIA) assumption of the MNL model to accommodate the correlation between adjacent time intervals (Ben-Akiva and Bierlaire, 1999; Börjesson, 2008; Chin, 1990; Lemp et al., 2010). Application of joint choice modelling, as estimated by Hendrickson and Plank (1984), and Hossain et al. (2021), simultaneously developed time-of-day choices alongside other travel decisions, such as mode choice. Habib et al. (2009) and Bhat (1998) used joint multinomial logit (MNL) and generalised extreme value (GEV) formulations for modelling mode and departure time choice models focusing on commuter and non-commuters' trips, respectively. Moreover, Li et al. (2018), De Jong et al. (2003) and Hess et al. (2007) used a mixed multinomial logit (MMNL) model to investigate joint mode and departure time choices capturing the correlation between alternatives which are close to each other. Heterogeneity in time-of-day choice by different market segments is also captured by the latent class choice models (Thorhauge et al., 2021). Additionally, Bayesian network and machine learning models have been explored for time-of-day choice analysis (Zhu et al., 2018).

The discrete choice models of departure time involve trade-offs between the time-of-day and associated travel time and costs. Outside of peak hours, the travel times are shorter, the congestion levels are lower, and the travel costs are often lower (e.g., off-peak public transport tickets). However, there can be an indirect cost associated with less convenient departure times, captured as 'Schedule Delay' (Börjesson, 2008, 2009). Due to the difficulties in simulating the preferred departure times, the schedule delay based technique performs well for exploratory modelling but is challenging for long-term forecasting applications (Hess et al., 2005). For the forecasting application, a more straightforward approach uses constants associated with different time periods to represent travellers' time preferences. However, specifying these constants is complex due to the number and length of time periods considered, limiting its applicability (Ben-Akiva and Abou-Zeid, 2013). Previous studies have used either a small number of coarse time periods or a large number of fine time periods, leading to increased computational costs and parameter identification issues. To address such issues, different studies have proposed functional approximation of the alternative specific constants (ASCs) (Ben-Akiva and Abou-Zeid, 2013; Hess et al., 2005). This approach offers several benefits to the model such as 1) reducing the computational cost by lowering the number of parameters to be estimated, 2) avoiding the identification issues associated with the discontinuities in the utility function and the absence of observations for some arrival and departure time periods in the data, and 3) facilitating the interpretation of the results. Various functional forms, such as trigonometric, piecewise linear, and power series expansion functions, have been proposed to estimate the distribution of these constants (Abou-Zeid et al., 2006; Ben-Akiva and Abou-Zeid, 2013; Hess et al., 2005). The constants used in the previous studies to capture the time preferences of travellers were related to three dimensions — outbound, return, and duration. However, their proposed specification employs two separate functional forms for outbound and return (or duration) times, thus overlooking the interdependency and correlations among departure time, duration, and return time. Inappropriate assumptions regarding the functional form may result in specification errors and introduce uncertainties in the model predictions (De Jong et al., 2007).

To accurately model the time-of-day preference, consideration of correlations and interactions between departure time and duration is crucial. Positive associations between departure time and duration may suggest a preference for later time-of-day choices as duration requirements increase, while negative associations may indicate an inclination towards earlier time-of-day choices. This hypothesis is grounded in the understanding that varying schedule constraints and the flexibility of working hours influence the perceived utility of different departure times for comparable activity durations (Ashiru et al., 2004; Badiola et al., 2019). Testing this hypothesis will provide valuable insights into the nuanced dynamics of time-of-day preferences in urban travel behaviour. This is because the utility of departing at 9 am for an 8-hour work period is not expected to be the same as departing at 3 pm for the same activity duration, owing to potential schedule constraints and the flexibility of working hours. Additionally, peak-hour outbound travel demand for 8–10 h of activity duration may lead to increased demand for return travel during peak hours. Similarly, the time-of-day choice during peak hours for a specific activity duration will not have the same impact on the network as it would during off-peak hours.

Therefore, in this study we proposed a polynomial functional form of ASCs that captures the correlation among the constants of the outbound, return (or duration) with an aim to improve the behavioural realism of the departure time choice models. The proposed structure is calibrated with data from Dhaka, one of the fastest growing megacities in the world and the capital of Bangladesh. The results of the proposed model are compared with those derived from the state-of-the-art method for capturing time-of-day preferences (based on the trigonometric formulation proposed by Ben-Akiva and Abou-Zeid (2013). This article aims to make two key contributions. Firstly, it introduces a flexible and efficient functional form of alternative specific constants (ASCs) that captures the interaction between departure time and duration preferences (which hasn't been done before) exemplified with, but not limited to commuting trips using a discrete choice framework. The proposed model framework is expected to serve as an improved tool for planners and policy makers in better understanding the preferences of the travellers and designing effective peak-spreading policies to reduce peak hour travel demand or promote off-peak travel. Secondly, it focuses on Dhaka (the sixth largest megacity in the world in terms of population) as a case study and suggests specific planning and policy measures for to reduce peak hour car travel demand. Further, while the specific findings may not be transferable to other developing countries, the modelling approach will offer valuable insights to transport planners and policymakers in overcoming the challenges of developing robust departure time choice models amidst data scarcity and limited resources.

The rest of the paper is organised as follows: the following section describes the data sources used in this study. The modelling issues are presented next, followed by the description of the model structure and the estimation results. The findings and forecasting analysis are summarised in the end, along with directions for future research.

2. Data

The review of the literature reveals that most of the previous departure time choice models have used stated preference (SP) (Arellana et al., 2012; Arellana et al., 2013; Azhdar and Nazemi, 2020; De Jong et al., 2003; Hess et al., 2007; Thorhauge et al., 2019) with a lower number using revealed preference (RP) datasets (Bhat, 1998; Chaichannawatik et al., 2019; Yang et al., 2008). Even though it is easier to specify the choice set and the preferred departure time in the SP, such data may be prone to hypothetical bias and behavioural incongruence (Ben-Akiva and Bierlaire, 2003; Bwambale et al., 2019).

We conducted our empirical investigation in the greater Dhaka area, specifically the RAJUK area. The RP data used in our study was obtained from a secondary data source, which was originally collected for a feasibility study of the subway project in Dhaka by TYPSA (DHAKA SUBWAY − Grupo TYPSA). This dataset included information from 35,000 households and was systematically collected using stratified random sampling to represent the population characteristics of the RAJUK area. The data was collected from Monday to Saturday[1] between 28th February 2019 to 4th May 2019. The survey form had two sections: (1) general household information (e.g., age, gender, education, occupation, income, car ownership), and (2) each household member's trip-related information (e.g., departure time, travel mode, travel time, trip purpose) who made any trips during the previous working day (Sunday to Thursday). The travel diary survey recorded trips for work, education, leisure, personal and other purposes. In the case where members of a selected household declined to participate in the interview, a nearby household with a similar socio-economic profile was chosen for the interview. This often involved selecting a household located in the same building as the one that declined to be interviewed. To enhance participation, a public awareness campaign was implemented for the household interview program. This campaign included strategies such as sending text messages to approximately 13 million people to encourage their participation, along with TV scrolls. The detailed methods employed by TYPSA to ensure that this sample accurately reflected the population characteristics can be found in (TYPSA, 2019).

The 35,000-household travel diary survey data included 1,37,760 trip information, of which only 4,003 involved car travel or ride-hailing services. The focus of our study was on work-related trips, and among the 4,003 observed car trips, 1,217 were for work purposes. Also, for the estimation of the joint departure time choice model, we only considered the work trips that began and ended at home, 950 trips met this screening criterion. As our primary data sources accurately reflected the overall population characteristics, our specific target group as a subsample effectively represents the car user population in Dhaka. It may be noted we excluded work trips originating from locations other than one's home and considered only car-based modes, as including all trips would have required a joint departure time, mode, and destination choice model, which was beyond the intended focus of this study. Since only a small number of individuals in the data reported multiple trips, we used one trip per person, with the earliest trips made by the commuters considered for this study. Commuting trips that had their origin outside Dhaka were not considered since that decision would be reliant on the traffic situation in the origin area. The socio-demographic characteristics of the commuters included in the sample are summarised in Table 1.

The observed departure time choices of commuters for their outbound and return trips, along with the corresponding duration (interval between outbound departure and return), are shown in Fig. 1 (a), Fig. 1(b), and Fig. 1(c). As seen in the figures, the departure time distribution for the return trips has a higher standard deviation compared to that of the outbound. For the outbound trips, the

[1] Friday is the weekly holiday in Bangladesh.

Table 1
Summary of socio-demographic characteristics of the commuters in the sample.

	Percentage
	Total respondents (n = 950)
Gender	
Male	83.16
Female	16.84
Age	
<26	4.00
26—40	37.68
40–60	47.47
>60	10.85
Monthly income	
<10,000 BDT	1.08
10,000–20,000 BDT	3.98
20,000–30,000 BDT	5.38
30,000–40,000 BDT	9.68
40,000–60,000 BDT	18.06
>60,000 BDT	61.82
Level of education	
Below primary	3.81
Six to ten	5.93
SSC	5.93
HSC	9.74
BA	18.00
MA	55.03
Others	1.56
Occupation	
Public Employee	20.63
Private employee	35.58
Self-employed	36.84
Other	6.95
Car ownership rate	
No car owned by the household*	12.11
Have at least one car owned by the household	87.89

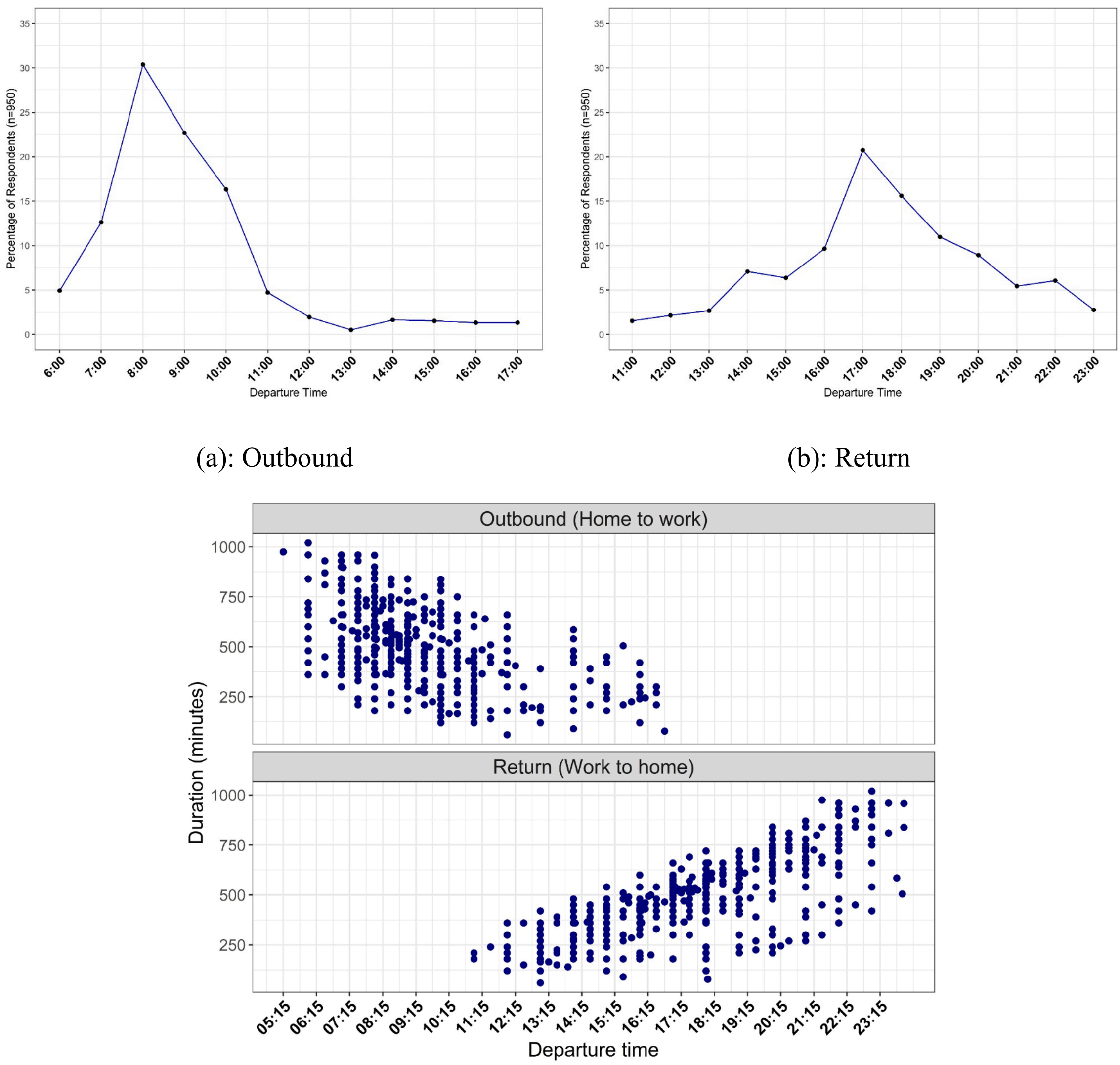
Source: (TYPSA, 2019).
* In this case, respondents were sharing cars with friends/colleagues or using cars provided from the office or ride-hailing services.

peak is observed at 8:00 and for the return trips, the peak is observed at 17:00. In terms of duration, for the majority of the travellers, the difference between the outbound and the return trips were between 6–10 h. The observed departure distribution indicates that for outbound trips, there is an earlier departure for longer durations, while for return trips, there is a later departure when the duration requirement is larger (Fig. 1(c)).

3. Modelling issues

3.1. Choice set specification

The choice set specification is a complex step in developing a discrete choice-based departure time choice model. At this stage, the number and length of time periods are determined by subdividing the continuous time into a finite number of mutually exclusive time periods. Studies have used either a small number of the coarse time periods or a large number of fine time periods. Ben-Akiva and Bierlaire (2003) proposed a method to define the acceptable range of departure time intervals based on the preferred arrival time (PAT). However, in RP data, information related to PAT is typically not available and overestimation of the time interval may cause substantial errors. Further, in a usual specification of a joint model (simultaneous consideration of both outbound and return), a separate constant is recommended for each possible combination of home to work (outbound) and work to home (inbound) time periods. For example, *24 (N)* 1-hour separate time periods for commuting trips would lead to a requirement of 300 constants (following the rule $N(N+1)/2$), of which 299 ($N(N+1)/2-1$) can be estimated (Hess et al., 2007)). Similarly, the required number of constants would be 1,176 if 30-minute time intervals are considered for 24 h. Thus, the increasing number of constants may lead to compounding problems of computational cost and parameter identification issues. Also, the correlation among the alternatives cannot be ignored when time intervals are short (Ben-Akiva and Bierlaire, 2003). Therefore, in this study, we have selected 9 time periods for outbound (6:00 – 7:00, 7:00 – 8:00, 8:00 – 9:00, 9:00 – 10:00, 10:00 – 11:00, 11:00 – 12:00, 12:00 – 14:00, 14:00 – 16:00, 16:00—17:00) and 9 periods for return (11:00 – 12:00, 12:00 – 14:00, 14:00 – 16:00, 16:00—17:00, 17:00 – 18:00, 18:00 – 19:00, 19:00 – 20:00, 20:00 – 22:00, 22:00——24:00. These time periods were divided into ten 1-hour time periods (6:00 – 7:00, 7:00 – 8:00, 8:00 – 9:00, 9:00 – 10:00, 10:00 – 11:00, 11:00 – 12:00, 16:00—17:00, 17:00 – 18:00, 18:00 – 19:00, 19:00 – 20:00) and four 2-hour time periods (12:00 – 14:00, 14:00 – 16:00, 20:00 – 22:00, 22:00 – 24:00). We opted not to use a finer temporal resolution (e.g., 5 to 10 min) to avoid



(a): Outbound (b): Return

(c) Duration

Fig. 1. Observed departure time.

correlation among alternatives of a short time interval and reduce model complexity. A total of 75 alternative outbound and return combinations of choice were specified. The choice set used in this study is summarised in Table 3. In order to forecast the probability of unchosen alternatives, all the joint combination of alternatives shown in Table 3 were included in the model.

Table 2
Summary of observed duration.

Duration window	Percentage
<2 h	3.01
2 h – 4 h	9.76
4 h – 6 h	14.64
6 h – 8 h	26.17
8 h – 10 h	27.12
10 h – 12 h	11.32
>=12 h	7.98

Table 3
Joint time periods (outbound and return) used for modelling.

ID	Outbound	Return	ID	Outbound	Return	ID	Outbound	Return	ID	Outbound	Return
1	6:00 – 7:00	11:00 – 12:00	20	8:00 – 9:00	12:00 – 14:00	39	10:00 – 11:00	14:00 – 16:00	58	12:00 – 14:00	17:00 – 18:00
2	6:00 – 7:00	12:00 – 14:00	21	8:00 – 9:00	14:00 – 16:00	40	10:00 – 11:00	16:00 – 17:00	59	12:00 – 14:00	18:00 – 19:00
3	6:00 – 7:00	14:00 – 16:00	22	8:00 – 9:00	16:00 – 17:00	41	10:00 – 11:00	17:00 – 18:00	60	12:00 – 14:00	19:00 – 20:00
4	6:00 – 7:00	16:00 – 17:00	23	8:00 – 9:00	17:00 – 18:00	42	10:00 – 11:00	18:00 – 19:00	61	12:00 – 14:00	20:00 – 22:00
5	6:00 – 7:00	17:00 – 18:00	24	8:00 – 9:00	18:00 – 19:00	43	10:00 – 11:00	19:00 – 20:00	62	12:00 – 14:00	22:00 – 24:00
6	6:00 – 7:00	18:00 – 19:00	25	8:00 – 9:00	19:00 – 20:00	44	10:00 – 11:00	20:00 – 22:00	63	14:00 – 16:00	14:00 – 16:00
7	6:00 – 7:00	19:00 – 20:00	26	8:00 – 9:00	20:00 – 22:00	45	10:00 – 11:00	22:00 – 24:00	64	14:00 – 16:00	16:00 – 17:00
8	6:00 – 7:00	20:00 – 22:00	27	8:00 – 9:00	22:00 – 24:00	46	11:00 – 12:00	11:00 – 12:00	65	14:00 – 16:00	17:00 – 18:00
9	6:00 – 7:00	22:00 – 24:00	28	9:00 – 10:00	11:00 – 12:00	47	11:00 – 12:00	12:00 – 14:00	66	14:00 – 16:00	18:00 – 19:00
10	7:00 – 8:00	11:00 – 12:00	29	9:00 – 10:00	12:00 – 14:00	48	11:00 – 12:00	14:00 – 16:00	67	14:00 – 16:00	19:00 – 20:00
11	7:00 – 8:00	12:00 – 14:00	30	9:00 – 10:00	14:00 – 16:00	49	11:00 – 12:00	16:00 – 17:00	68	14:00 – 16:00	20:00 – 22:00
12	7:00 – 8:00	14:00 – 16:00	31	9:00 – 10:00	16:00 – 17:00	50	11:00 – 12:00	17:00 – 18:00	69	14:00 – 16:00	22:00 – 24:00
13	7:00 – 8:00	16:00 – 17:00	32	9:00 – 10:00	17:00 – 18:00	51	11:00 – 12:00	18:00 – 19:00	70	16:00 – 17:00	16:00 – 17:00
14	7:00 – 8:00	17:00 – 18:00	33	9:00 – 10:00	18:00 – 19:00	52	11:00 – 12:00	19:00 – 20:00	71	16:00 – 17:00	17:00 – 18:00
15	7:00 – 8:00	18:00 – 19:00	34	9:00 – 10:00	19:00 – 20:00	53	11:00 – 12:00	20:00 – 22:00	72	16:00 – 17:00	18:00 – 19:00
16	7:00 – 8:00	19:00 – 20:00	35	9:00 – 10:00	20:00 – 22:00	54	11:00 – 12:00	22:00 – 24:00	73	16:00 – 17:00	19:00 – 20:00
17	7:00 – 8:00	20:00 – 22:00	36	9:00 – 10:00	22:00 – 24:00	55	12:00 – 14:00	12:00 – 14:00	74	16:00 – 17:00	20:00 – 22:00
18	7:00 – 8:00	22:00 – 24:00	37	10:00 – 11:00	11:00 – 12:00	56	12:00 – 14:00	14:00 – 16:00	75	16:00 – 17:00	22:00 – 24:00
19	8:00 – 9:00	11:00 – 12:00	38	10:00 – 11:00	12:00 – 14:00	57	12:00 – 14:00	16:00 – 17:00			

3.2. Factors influencing departure time choice

Departure time choices depend on multiple factors that are interrelated to each other. Earlier studies examined the influence of travellers' choice decisions as a function of transportation system characteristics and level of service attributes (e.g. travel time, travel cost), individual and household sociodemographic characteristics, activity-related attributes (e.g. mandatory vs. discretionary) (Bhat and Steed, 2002; Sasic and Habib, 2013). Findings of the previous studies show that the departure time choice of individuals is substantially affected by travel time, travel cost and travel distance which are often marked as the level of service attributes or network variables (Abou-Zeid et al., 2006; Arellana et al., 2012; Ben-Akiva et al., 1985; Zhu et al., 2018). Other studies have investigated the influence of schedule delay on departure time choice (Börjesson, 2008, 2009; Bwambale et al., 2019; Hess et al., 2005; Koppelman et al., 2008; Yang and Liu, 2018). Other contributing factors include individual (e.g. age, gender, level of education, having a driving license, working status, flexibility at work etc.) and household attributes (e.g. household size, income, vehicle ownership, house location) (Afandizadeh Zargari and Safari, 2020; Anowar et al., 2019; Arellana et al., 2013; Bhat and Steed, 2002; Rahman et al., 2021; Yang et al., 2008).

Based on the review, the level of service attributes (travel time), individual (age, gender, occupation, education) and household (household income, house location, household size, having dependant within the household) sociodemographic characteristics and trip-related attributes (available mode, distance) were considered in both the proposed and trigonometric model by (Ben-Akiva and Abou-Zeid, 2013).

3.3. Estimation of travel time

One of the key challenges to model departure time choice is the estimation of travel time during the unchosen time periods. In many cities, Google Maps and, Open Street Maps provide reliable travel times for each alternative time period with adequate spatial and temporal granularity which can be used for deriving travel times during different time periods for different origin–destination pairs (e.g. Bwambale et al. (2019) and Dong and Cirillo (2020)). But in the context of Dhaka, the widely used network traffic model of Google Maps API (i.e., best guess) does not consistently reflect a reasonable travel time that matches the users' experienced travel time. Instead, it offers three network travel times for each origin-destination pair within a given time period (best guess,[2] pessimistic,[3] optimistic[4]). At some time period, the travel time from the pessimistic model appears to be more closely aligned with the user-stated travel time, while in other instances, the other two models demonstrate better alignment. Therefore, we estimated the travel time for both chosen and unchosen time period following the method proposed by Zannat et al. (2021) who hypothesised that the commuter stated travel time is linearly correlated with the predicted travel time of Google map direction API. The relationship between stated travel time and the best guess, pessimistic and optimistic travel times can be expressed as follows:

[2] Best guess model returns the duration in traffic using both historical traffic conditions and live traffic. Live traffic becomes more important the closer the departure time is to now.

[3] Pessimistic model returns the duration in traffic, usually that should be longer than the actual travel time on most days, though occasional days with particularly bad traffic conditions may exceed this value.

[4] Optimistic model returns the duration in traffic, usually that should be shorter than the actual travel time on most days, however, occasional days often with a good traffic condition could be faster than this value.

$$T_{stated\ travel\ time\_i} = W_{i,1}T_{Best\ guess\_i} + W_{i,2}T_{Optimistic\_i} + W_{i,3}T_{Pessimistic\_i} + \varepsilon \quad (1)$$

where,

i is the alternative time period ($i \in n$, where n is 7 for home to work and 5 for work to home trip)

$T_{stated\ travel\ time\_i}$ = Stated travel time by the respondents at the time period i.

$T_{Best\ guess\_i}$ = Measured travel time using best guess model of google direction API at the time period i.

$T_{Optimistic\_i}$ = Measured travel time using optimistic model of google direction API at the time period i.

$T_{Pessimistic\_i}$ = Measured travel time using pessimistic model of google direction API at the time period i.

$W_{i,t}$ indicates the weights of measured travel time by different Google map models (t) for time period i, $W_{i,1}$, $W_{i,2}$, and $W_{i,3}$ were estimated assuming $\sum W_{i,t} = 1$. ε represents the error which is assumed to be normally distributed (0, σ). The relationship among $W_{i,t}$

Table 4
Calculated weights of the different model used for travel time calculation.

(a) Home to Work Trip				
Home to Work Trip	**Google Maps Model**	**Estimates ($\beta_{i,t}$)**	**Exp ($\beta_{i,t}$)**	**Weight ($Å_{i,t}$)**
		$\sigma = 31.4626$		
6:00 – 7:00	Best Guess	14.2567	1554555.173	0.9996[(a)]
	Optimistic	6.4678	644.0652237	0.0004
	Pessimistic	0	1	0.0000
		$\sum$	1555200.238	1
7:00 – 8:00	Best Guess	−15.9892	1.13757E-07	0.0000
	Optimistic	1.1985	3.315140481	0.7683
	Pessimistic	0	1	0.2317
		$\sum$	4.315140594	1
8:00 – 9:00	Best Guess	−12.567	3.48515E-06	0.0000
	Optimistic	0.239	1.269978537	0.5595
	Pessimistic	0	1	0.4405
		$\sum$	2.269982022	1
9:00 –10:00	Best Guess	−12.567	3.48515E-06	0.0000
	Optimistic	0.239	1.269978537	0.5595
	Pessimistic	0	1	0.4405
		$\sum$	2.269982022	1
10:00 – 11:00	Best Guess	−1.8409	0.158674555	0.0559
	Optimistic	0.5177	1.678163432	0.5916
	Pessimistic	0	1	0.3525
		$\sum$	2.836837986	1
11:00 – 12:00	Best Guess	0.0022	1.002202422	0.4997
	Optimistic	−5.6696	0.003449245	0.0017
	Pessimistic	0	1	0.4986
		$\sum$	2.005651666	1
12:00 and after 12:00	Best Guess	−0.7994	0.449598642	0.0000
	Optimistic	17.0538	25490082.17	1.0000[(b)]
	Pessimistic	0	1	0.0000
		$\sum$	25490083.62	1
(b) Work to Home Trip				
Work to Home trip	**Google Maps Model**	**Estimates ($\beta_{i,t}$)**	**Exp ($\beta_{i,t}$)**	**Weight ($Å_{i,t}$)**
11:00 – 12:00	Best Guess	0.0022	1.002202422	0.4997
	Optimistic	−5.6696	0.003449245	0.0017
	Pessimistic	0	1	0.4986
		$\sum$	2.005651666	1
12:00 – 14:00	Best Guess	1.763	5.829900889	0.0009
	Optimistic	8.7768	6482.101226	0.9989[(c)]
	Pessimistic	0	1	0.0002
		$\sum$	6488.931127	1
16:00 – 18:00	Best Guess	−9.1197	0.000109488	0.0001
	Optimistic	−1.7165	0.179693977	0.1523
	Pessimistic	0	1	0.8476
		$\sum$	1.179803465	1
18:00 – 19:00	Best Guess	−5.1375	0.005872352	0.0007
	Optimistic	2.0616	7.85853341	0.8865
	Pessimistic	0	1	0.1128
		$\sum$	8.864405762	1
19:00 – 24:00	Best Guess	7.1876	1322.924374	0.9880
	Optimistic	2.7108	15.04130375	0.0112
	Pessimistic	0	1	0.0007
		$\sum$	1338.965678	1

Note: Given the close to 1 weight, only the Best Guess model has been used in (a) and only the Optimistic model has been used in (b) and (c) instead of the weighted models.

and estimated parameters for different models (t) at time period i can be expressed as:

$$W_{i,t} = \frac{e^{\beta_{i,t}}}{e^{\beta_{i,1}} + e^{\beta_{i,2}} + e^{\beta_{i,3}}} \tag{2}$$

Following the normal distribution, equation (1) and equation (2) was used to estimate $\beta_{i,t}$ for three Google maps models. Consequently, we calculated the weighted network travel time using the estimated weight $Å_{i,t}$ corresponding to various network models rather than relying on the network travel time from the randomly selected network model (t) using the Google Map API. The network travel time for all alternatives was estimated using the Equation (3). Models and their corresponding weights used for the different alternative time periods are shown in Table 4.:

$$T_{network\ travel\ time\_i} = Å_{i,1} T_{Best\ guess\_i} + Å_{i,2} T_{Optimistic\_i} + Å_{i,3} T_{Pessimistic\_i} \tag{3}$$

4. Model structure

4.1. Framework

The proposed model structure is based on random utility framework. Random utility theory suggests that individual decision is driven by rationality and complete information. Decision-makers choose the departure time that provides them with the highest utility, where the utility of an alternative i to a person n has the form:

$$U_{in} = U(x_{in}, s_n) \tag{4}$$

where x_{in} is the vector of the attribute of alternative i for individual n and s_n is the vector of characteristics of individual n.

McFadden (1973) proposed that this utility has the linear-in-parameters separable form:

$$U_{in} = V_{in} + \varepsilon_{in} \tag{5}$$

where V_{in} is the observed component of utility. The unobserved variable ε_{in} expresses the contribution of unobserved attributes to the utility. In our model, ε_{in} is assumed to be independent and identically distributed across alternatives and respondents, following a Type I Extreme Value distribution (Gumbel). Therefore, the time preference of commuters is estimated using the multinomial logit model (MNL).

Further, following our proposed polynomial formulation, for an alternative time period (departure time period for outbound o, departure time period for return r), the systematic utility for the home-based commuting trip can be specified as sum of three components corresponding to the outbound departure time (${V_{in}}^{dept}$), the duration (${V_{in}}^{dur}$) and the interaction between two (${V_{in}}^{int}$).

$$V_{in} = {V_{in}}^{dept} + {V_{in}}^{dur} + {V_{in}}^{int} \tag{6}$$

where, ${V_{in}}^{dept}$, ${V_{in}}^{dur}$, ${V_{in}}^{int}$ can be specified as follows:

$${V_{in}}^{dept} = \sum_{k=1}^{4} s_k f^{dept}(t_o) + \beta(TT_o) \tag{7}$$

$${V_{in}}^{dur} = \sum_{k=1}^{4} s_k f^{dur}(t_r - t_o) + \beta(TT_r) \tag{8}$$

$${V_{in}}^{int} = \sum_{k=1}^{4} s_k f^{int}(t_o)(t_r - t_o) \tag{9}$$

where, t_o and t_r are the departure times from home for outbound (midpoint of period o) and return

respectively (midpoint of period r). Also, $s_1 = 1$, $s_2 =$ office employee dummy, $s_3 =$ short distance dummy (<8 km), $s_4 =$ High income dummy (>60,000 BDT) and TT_o and TT_r are the corresponding travel time of outbound and return.

The proposed polynomial formulation for departure time, duration and interaction can be expressed as follows:

$$f^{dept}(t_o) = {\alpha_1}^{dept} t_o + {\alpha_2}^{dept} {t_o}^2 + \cdots + {\alpha_a}^{dept} {t_o}^a \tag{10}$$

$$f^{dur}(t_r - t_o) = {\alpha_1}^{dur}(t_r - t_o) + {\alpha_2}^{dur}(t_r - t_o)^2 + \cdots + {\alpha_b}^{dur}(t_r - t_o)^b \tag{11}$$

$$f^{int}(t_o)(t_r - t_o) = {\alpha_i}^{int}(t_o)(t_r - t_o) \tag{12}$$

where a, and b are non-negative integer values defining truncation points and are determined empirically.

The unknown parameter to be estimated in the polynomial formulation are: ${\alpha_1}^{dept}$, ⋯, ${\alpha_a}^{dept}$, ${\alpha_1}^{dur}$, ⋯, ${\alpha_b}^{dur}$ and ${\alpha_i}^{int}$, for every variable s_k that is interacted with $f^{dept}(t_o)$, $f^{dur}(t_r - t_o)$ and $f^{int}(t_o)(t_r - t_o)$ in the departure time, duration and interaction component of utility function, and the travel time parameter β. However, for every variable s_k, we estimated four different interaction parameters for — 1) alternatives with peak time at both legs (outbound and return), 2) alternatives with peak time at outbound leg, 3) alternatives with peak time at return leg and, 4) alternatives with off-peak time at both legs. Such specification enabled to capture the correlation between departure time and duration, and schedule delay effect simultaneously.

The choice probabilities for each alternative i in MNL can be expressed as follows (for detail see Train (2009)):

$$P_{in} = \frac{exp\left(V_{in}{}^{dept} + V_{in}{}^{dur} + V_{in}{}^{int}\right)}{\sum_{j \in C_n} exp\left(V_{jn}{}^{dept} + V_{jn}{}^{dur} + V_{jn}{}^{int}\right)} \tag{13}$$

where, C_n is the choice set of n number of individuals (see section 3.1 for details).

The estimation has been done using the "Apollo" package R, applying the Maximum Likelihood Estimation technique with the BFGS optimisation algorithm (Hess and Palma, 2019).

4.2. Trigonometric model

The trigonometric formulation proposed by Ben-Akiva and Abou-Zeid (2013) was used as the state-of-the-art model. Following this model, the systematic utility for the home-based commuting trip can be specified as sum of departure time component for outbound, departure time component for return and associated duration component. Hence,

$$V_{in} = V_{in}{}^{out} + V_{in}{}^{ret} + V_{in}{}^{dur} \tag{14}$$

here, $V_{in}{}^{out}$, $V_{in}{}^{ret}$ and $V_{in}{}^{dur}$ are the outbound, return and duration component of utility.

$V_{in}{}^{out}$ and $V_{in}{}^{ret}$ are then specified as follows:

$$V_{in}{}^{out} = \sum_{k=1}^{4} s_k f^{out}(t_o) + \ln(number\ of\ 1\ hour\ in\ period\ o) + \beta\,(TT_o) \tag{15}$$

$$V_{in}{}^{ret} = \sum_{k=1}^{4} s_k f^{ret}(t_r) + +\ln(number\ of\ 1\ hour\ in\ period\ r) + \beta\,(TT_r) \tag{16}$$

The trigonometric formulation for outbound and return can be expressed as follows:

Table 5
Estimates from the base MNL model.

(a) State-of-the-art model			(b) Proposed model		
Parameter	Estimate	Rob.t.rat.(0)	Parameter	Estimate	Rob.t.rat.(0)
$\alpha_1{}^{out}$	3.025	8.732	$\alpha_1{}^{dept}$	8.210	8.124
$\alpha_2{}^{out}$	3.257	7.223	$\alpha_2{}^{dept}$	−0.683	−7.647
$\alpha_3{}^{out}$	−1.740	−4.694	$\alpha_3{}^{dept}$	0.018	7.174
$\alpha_4{}^{out}$	−1.729	−6.543	$\alpha_1{}^{dur}$	1.748	8.555
$\alpha_5{}^{out}$	0.970	5.045	$\alpha_2{}^{dur}$	−0.126	−6.869
$\alpha_6{}^{out}$	−1.970	−10.403	$\alpha_3{}^{dur}$	0.004	5.269
$\alpha_7{}^{out}$	−2.440	−6.874	$\alpha^{int}out\&retoffpeak$	−0.046	−4.761
$\alpha_8{}^{out}$	−1.016	−5.470	$\alpha^{int}outpeak$	−0.043	−4.392
$\alpha_1{}^{ret}$	−2.488	−3.424	$\alpha^{int}retpeak$	−0.047	−4.582
$\alpha_2{}^{ret}$	2.291	4.206	$\alpha^{int}out\&retpeak$	−0.034	−3.333
$\alpha_3{}^{ret}$	−0.319	−2.678	β_{TT}	−0.012	−3.707
$\alpha_4{}^{ret}$	−1.233	−4.049			
$\alpha_5{}^{ret}$	−1.197	−7.084			
$\alpha_6{}^{ret}$	−1.657	−7.118			
$\alpha_7{}^{ret}$	1.878	4.381			
$\alpha_8{}^{ret}$	−1.300	−2.658			
$\alpha_1{}^{dur}$	0.642	3.064			
$\alpha_2{}^{dur}$	−0.092	−4.151			
$\alpha_3{}^{dur}$	0.003	3.665			
$\boldsymbol{\beta_{TT}}$	**−0.009**	**−2.515**			
LL (0)	−4101.61	LL (0)	−4101.61		
LL (final)	−3651.42	LL (final)	−3655.72		
Rho-square (0)	0.1098	Rho-square (0)	0.1087		
Adj.Rho-square	0.1049	Adj.Rho-square	0.106		
AIC	7342.84	AIC	7333.43		
BIC	7439.97	BIC	7386.86		
RMSE	5.35	RMSE	4.58		
Estimated parameters	20	Estimated parameters	11		

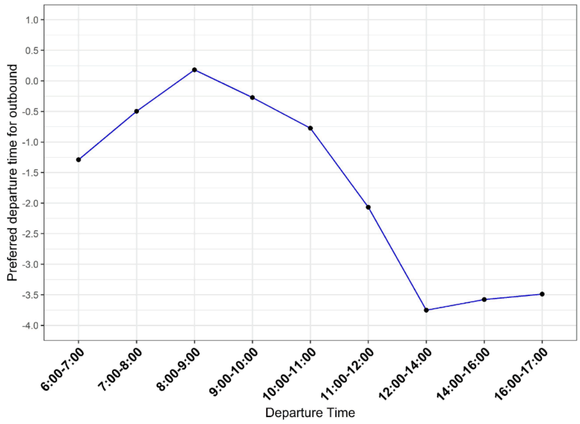
$$f^{out}(t_o) = \alpha_1{}^{out}\sin\left(\frac{2\pi t_o}{24}\right) + \alpha_2{}^{out}\sin\left(\frac{4\pi t_o}{24}\right) + \alpha_3{}^{out}\sin\left(\frac{6\pi t_o}{24}\right) + \alpha_4{}^{out}\sin\left(\frac{8\pi t_o}{24}\right) + \alpha_5{}^{out}\cos\left(\frac{2\pi t_o}{24}\right) + \alpha_6{}^{out}\cos\left(\frac{4\pi t_o}{24}\right) + \alpha_7{}^{out}\cos\left(\frac{6\pi t_o}{24}\right) + \alpha_8{}^{out}\cos(\frac{8\pi t_o}{24}) \tag{17}$$

$$f^{ret}(t_r) = \alpha_1{}^{ret}\sin\left(\frac{2\pi t_r}{24}\right) + \alpha_2{}^{ret}\sin\left(\frac{4\pi t_r}{24}\right) + \alpha_3{}^{ret}\sin\left(\frac{6\pi t_r}{24}\right) + \alpha_4{}^{ret}\sin\left(\frac{8\pi t_r}{24}\right) + \alpha_5{}^{ret}\cos\left(\frac{2\pi t_r}{24}\right) + \alpha_6{}^{ret}\cos\left(\frac{4\pi t_r}{24}\right) + \alpha_7{}^{ret}\cos\left(\frac{6\pi t_r}{24}\right) + \alpha_8{}^{ret}\cos(\frac{8\pi t_r}{24}) \tag{18}$$

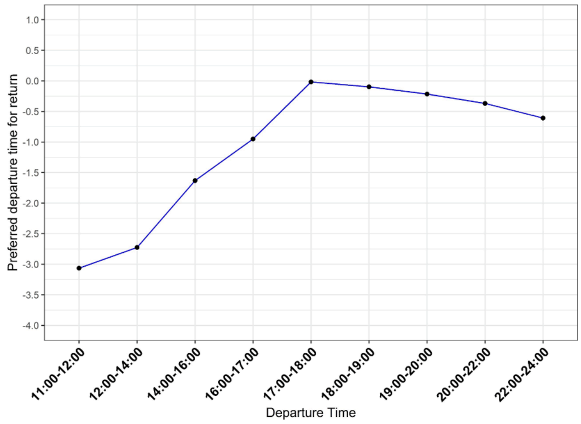
The duration component $V_{in}{}^{dur}$ is specified as a power series expansion as follows:

$$V_{in}{}^{dur} = \alpha_1{}^{dur}(t_r - t_o) + \alpha_2{}^{dur}(t_r - t_o)^2 + \cdots + \alpha_b{}^{dur}(t_r - t_o)^b \tag{19}$$

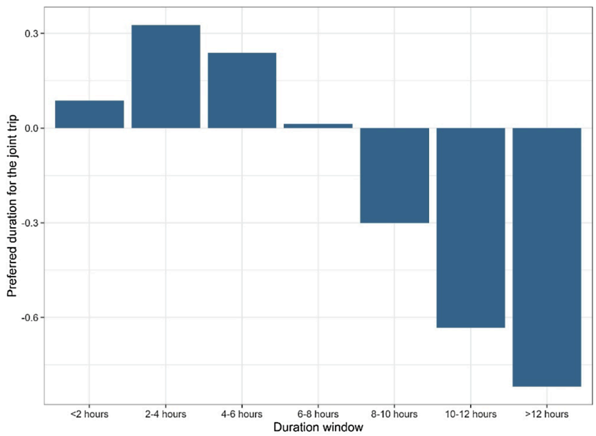
The unknown parameters to be estimated in the trigonometric formulation are: $\alpha_1{}^{out}, \cdots., \alpha_8{}^{out}$ and $\alpha_1{}^{ret}, \cdots, \alpha_8{}^{ret}$ for every variable s_k interacted with $f^{out}(t_o), f^{ret}(t_r)$ in the utility function, and the travel time parameter β. From the power expansion of duration utility, the estimated parameters are $\alpha_1{}^{dur}, \cdots, \alpha_b{}^{dur}$. Here, the b value depends on empirical consideration. Also, the size variable is included for the outbound and return departure time period. Similar to our proposed model, the estimates are estimated using the Maximum Likelihood Estimation technique.



(a) Intrinsic preference of departure time of outbound car commuters



(b) Intrinsic preference of departure time of return car commuters



(c) Intrinsic preference of duration

Fig. 2. Values of ASCs for (a) outbound, (b) return, and (c) duration following the trigonometric formulation (while controlling travel time sensitivity).

5. Results and discussion

5.1. Base MNL models

Table 5 shows the estimates of the simple MNL models fitted to the RP data developed using the state-of-the-art method and proposed polynomial formulation. These two base models were used to investigate the performance and interpretation capabilities of the proposed polynomial functional form. The models included travel time as the main explanatory variable, while other covariates (e.g., socio-demographic characteristics) were excluded. When comparing the adjusted Rho-square, and BIC, the results showed that the polynomial model produced a slightly better model fit than the trigonometric model. Additionally, the proposed model's RMSE value demonstrated that it had less error than the trigonometric model. This study also revealed that the polynomial approximation performed better than the trigonometric model when evaluating how travel time affected decisions. In the trigonometric model as opposed to the proposed model, the estimated marginal utility of trip time was lower. Also, in the proposed model, the interaction parameters were found to be statistically significant in modelling the time choice of travellers (the null hypothesis of zero correlations between departure times and durations was rejected at a 95 % level of confidence). The estimated coefficients of interaction parameters demonstrated that, within a time budget of 24 h per day, if car travellers chose a longer duration (including travel time to workplace and activity duration), they were less likely to prefer a later time of the day for departing from home. Moreover, the relatively lower interaction effect on those alternatives having peak time in both legs (outbound and return) reflected the lower schedule delay compared to the other alternatives.

The inferred shape of the ASCs' value from the trigonometric formulation (Fig. 2 (a) and Fig. 2 (b)) indicated potential overfitting of the models during the afternoon for outbound, and late evening for return journeys. This is likely attributed to the observation that late night alternatives for returning were not as popular as the afternoon and morning alternatives, respectively. Similarly, for outbound, the evening was the least popular than the other alternatives (Fig. 1). On the other hand, the aggregated utility of the duration component (estimated using power expansion) of the state-of-the-art method revealed that the highest utility was likely to be at the duration window between 2–4 h (Fig. 2 (c)). But the observation shows that the highest percentage of respondents chose the duration between 8–10 h (Table 2).

Fig. 3 shows a surface plot derived from the proposed polynomial formulation, to investigate the influence of outbound, duration and corresponding correlation, all together. All else being equal, the combination of time choices for outbound and return journeys were ranked as follows according to the level of preference: (1) 9:00 – 10:00 and 18:00 – 19:00, (2) 9:00 – 10:00 and 17:00 – 18:00, and (3) 8:00 – 9:00 and 17:00 – 18:00. Such results indicated that the utility of departure from home was higher between 8:00 – 10:00 and 17:00 – 19:00 for departure from work, which complied with the observed departure times (Fig. 1(a) and Fig. 1 (b)). At the same time, the preferred duration was greater than 9 h (estimated from the mid-point difference of return and outbound alternatives) which included the travel time to the workplace and activity duration. This result is intuitive because, in Bangladesh, the earliest office starting time is between 9:00 to 10:00 and closing time is between 16:00 to 17:00 which gives an average of 8 working hours (including

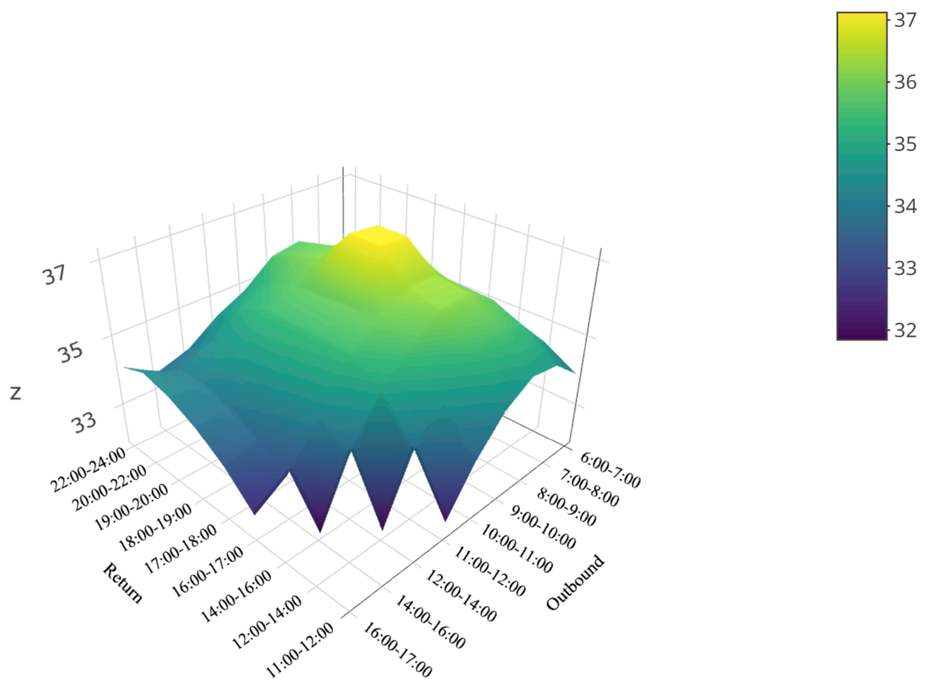


Fig. 3. Values of ASCs following the polynomial formulation while controlling travel time sensitivity (Highest utility at outbound 8:00 – 10:00 and return 17:00 – 19:00 combination).

lunch break). Therefore, from the base model, we can infer that our results comply with reality and the proposed model is appropriately fitted with the RP data of car commuters both in the morning and evening.

5.2. Comprehensive MNL models with sociodemographic factors

Separate MNL models were developed using both the trigonometric model by Ben-Akiva and Abou-Zeid (2013) and the proposed polynomial formulation where base models interacted with socio-demographic variables. Three different socio-demographic factors were considered using dummy variables that interacted with the constants of the base MNL models: occupation, trip-related attributes (e.g., trip length), and household income level. The resultant performance assessment indicators and estimates of both models are summarised in Table 6 and Table 7, respectively. The inclusion of socio-demographic variables with the base model led to a significant gain over the base model. The log-likelihood of trigonometric formulation increased by 121.46 over the base MNL model while incorporating 34 additional parameters for sociodemographic factors. On the other hand, the log-likelihood of the proposed polynomial formulation increased by 110.68 over the base MNL model with 24 additional parameters. The log-likelihood ratio test (LR) shows a significant improvement compared to the base MNL model (Table 6). However, the significance of the proposed formulation was distinguishable while comparing the adjusted rho-square, BIC and RMSE of both models (Table 6). The RMSE of the proposed model was lower than the RMSE of the trigonometric model, showing that the proposed polynomial model had less error than the trigonometric model. The intrinsic preference of departure time for different socio-demographic group is shown graphically for both state-of-the-art model and proposed model (Fig. 4 and Fig. 5).

5.2.1. Results from the model developed using trigonometric model

Results of the trigonometric model are presented in Fig. 4a, Fig. 4b, and Table 7 (a). Fig. 4a,b shows that the utility of outbound travel for all car commuters was larger between 7:00 and 10:00. Compared to the self-employed travellers, the office employees had higher utilities of departure for outbound trips between 8:00 – 9:00, followed by 7:00 – 8:00. The highest utility of departure for outbound trips of short distance travellers was between 8:00 – 10:00 compared to the long-distance travellers. The high-income households were more likely to prefer the morning peak (8:00 – 9:00) and a later time in the morning (10:00 – 11:00) for outbound trips compared to the commuters with a monthly household income below 60,000 BDT. Fig. 4b shows the intrinsic preferences of departure times for return trips among different socio-demographic groups formulated using the estimated values of ASCs using trigonometric formulation (while controlling travel time sensitivity). The return trips were less heterogeneous across different groups. The preference of departure was similar for short-distance car commuters and commuters from high-income households, while the pattern of the utility of office employees was different. For office employees, the utility of departure for return trips was higher between 17:00 – 18:00 than that of self-employed commuters. However, other groups such as short-distance travellers and high income had a higher utility of departure for return after 19:00.

5.2.2. Results from the model developed using the proposed polynomial formulation

Results from the model developed using the polynomial formulation are shown in Table 7 (b). Surface plots in Fig. 5 (a-d) show the preference of outbound, return, and duration for different socio-demographic groups while controlling travel time sensitivity. The results indicated that the interaction coefficients of outbound and duration varied across different socio-demographic groups. For example, office employees and people from high-income households were more sensitive to interaction effects compared to other groups. The inclusion of interaction parameters for different socio-demographics nulled the significance of the base interaction parameters, highlighting the heterogeneity in interaction effects among the different socio-demographic groups.

The base surface plot (Fig. 5 (a)) indicates that, for the reference group (e.g., self-employed personnel, long distance commuters, and respondents from high-income households), the preferred time choice for the car commuters was 9:00 – 10:00 and 18:00 – 19:00, followed by 9:00 – 10:00 and 17:00—–18:00, 8:00 – 9:00 and 17:00—–18:00, 8:00 – 9:00 and 18:00—–19:00. In terms of activity duration, the preferred duration choice varied from 8 to 10 h (includes activity duration and travel time to work). More than 46 % of car commuters (among the selected respondents) chose a duration window of greater than 8 h (Table 2).

Table 6
Performance statistics of comprehensive MNL models.

Model Parameters	(a) State-of-the-art model	(b) Proposed model
Number of observations	950	950
Number of estimated parameters	54	35
LL (0)	−4101.61	−4101.61
LL (final)	−3529.96	−3545.04
Rho-square (0)	0.1374	0.1357
Adj.Rho-square	0.1262	0.1272
AIC	7167.92	7160.08
BIC	7430.17	7330.05
RMSE	4.70	4.43
LR test result (Model with sociodemographic variables vs. base model)		
Likelihood ratio test-value (χ^2)	242.92	221.36
Degrees of freedom	34	24
P-value	2.196e-33	7.259e-34

Table 7
Estimates from comprehensive MNL model.

(a) State-of-the-art model

Parameter	Estimate	Rob.t.rat.(0)
α_1^{out}	2.393	5.762
α_2^{out}	2.889	5.887
α_3^{out}	−1.443	−3.477
α_4^{out}	−1.280	−3.740
α_5^{out}	0.585	2.192
α_6^{out}	−1.330	−5.542
α_7^{out}	−2.051	−5.038
α_8^{out}	−0.886	−3.032
α_1^{ret}	−2.794	−2.999
α_2^{ret}	2.549	3.676
α_3^{ret}	−0.360	−2.871
α_4^{ret}	−1.029	−2.722
α_5^{ret}	−0.795	−3.614
α_6^{ret}	−1.384	−4.772
α_7^{ret}	2.307	4.138
α_8^{ret}	−1.848	−2.922
$\alpha_2^{out*}\ s_2$	0.690	4.166
$\alpha_3^{out*}\ s_2$	−1.359	−8.122
$\alpha_4^{out*}\ s_2$	0.505	2.729
$\alpha_5^{out*}\ s_2$	−0.610	−2.684
$\alpha_8^{out*}\ s_2$	−1.209	−3.185
$\alpha_1^{ret*}\ s_2$	−0.627	−2.775
$\alpha_2^{ret*}\ s_2$	0.672	3.463
$\alpha_4^{ret*}\ s_2$	−0.613	−3.293
$\alpha_5^{ret*}\ s_2$	−0.538	−3.807
$\alpha_6^{ret*}\ s_2$	−0.900	−5.592
$\alpha_7^{ret*}\ s_2$	0.634	2.762
$\alpha_1^{out*}\ s_3$	0.242	1.559
$\alpha_4^{out*}\ s_3$	−0.213	−1.495
$\alpha_5^{out*}\ s_3$	0.121	0.919
$\alpha_6^{out*}\ s_3$	−0.342	−3.220
$\alpha_1^{ret*}\ s_3$	1.024	3.114
$\alpha_2^{ret*}\ s_3$	−0.810	−3.006
$\alpha_4^{ret*}\ s_3$	0.505	2.722
$\alpha_5^{ret*}\ s_3$	0.246	1.640
$\alpha_6^{ret*}\ s_3$	0.238	1.245
$\alpha_7^{ret*}\ s_3$	−0.872	−2.873
$\alpha_8^{ret*}\ s_3$	0.589	2.409
$\alpha_1^{out*}\ s_4$	0.886	3.877
$\alpha_3^{out*}\ s_4$	0.819	4.828
$\alpha_4^{out*}\ s_4$	−0.980	−3.319
$\alpha_5^{out*}\ s_4$	1.115	3.589
$\alpha_6^{out*}\ s_4$	−0.970	−3.798
$\alpha_7^{out*}\ s_4$	−0.590	−2.620
$\alpha_8^{out*}\ s_4$	0.553	1.483
$\alpha_1^{ret*}\ s_4$	0.524	2.200
$\alpha_2^{ret*}\ s_4$	−0.444	−2.348
$\alpha_5^{ret*}\ s_4$	−0.423	−3.490
$\alpha_7^{ret*}\ s_4$	−0.544	−2.779
$\alpha_8^{ret*}\ s_4$	0.466	2.254
α_1^{dur}	0.683	3.312
α_2^{dur}	−0.096	−4.580
α_3^{dur}	0.003	4.125
β_{TT}	−0.012	−3.336

(b) Polynomial formulation

Parameter	Estimate	Rob.t.rat.(0)
α_1^{dept}	7.508	3.555
α_2^{dept}	−0.640	−3.445
α_3^{dept}	0.017	3.208
α_1^{dur}	0.416	1.422
α_2^{dur}	−0.039	−1.53
α_3^{dur}	0.001	1.221
$\alpha^{int} out\&retoffpeak$	−0.002	−0.132
$\alpha^{int} outpeak$	6.7493e-04	0.041
$\alpha^{int} retpeak$	−0.003	−0.195
$\alpha^{int} out\&retpeak$	0.004	0.245
$\alpha_1^{dept*}\ s_2$	5.372	2.539
$\alpha_2^{dept*}\ s_2$	−0.507	−2.702
$\alpha_3^{dept*}\ s_2$	0.015	2.875
$\alpha_1^{dur*}\ s_2$	1.283	3.206
$\alpha_2^{dur*}\ s_2$	−0.080	−2.353
$\alpha_3^{dur*}\ s_2$	0.002	1.730
$\alpha^{int} out\&retoffpeak^*\ s_2$	−0.049	−2.404
$\alpha^{int} outpeak^*\ s_2$	−0.046	−2.210
$\alpha^{int} retpeak^*\ s_2$	−0.045	−2.124
$\alpha^{int} out\&retpeak\ s_2$	−0.038	−1.777
$\alpha_1^{dept*}\ s_3$	−5.766	−3.845
$\alpha_2^{dept*}\ s_3$	0.499	3.625
$\alpha_3^{dept*}\ s_3$	−0.013	−3.322
$\alpha_1^{dur*}\ s_3$	0.768	2.686
$\alpha_2^{dur*}\ s_3$	−0.075	−2.186
$\alpha_3^{dur*}\ s_3$	0.002	1.935
$\alpha_1^{dept*}\ s_4$	6.074	2.884
$\alpha_2^{dept*}\ s_4$	−0.465	−2.497
$\alpha_3^{dept*}\ s_4$	0.012	2.217
$\alpha_1^{dur*}\ s_4$	0.838	3.130
$\alpha_2^{dur*}\ s_4$	−0.026	−3.780
$\alpha^{int} out\&retoffpeak^*\ s_4$	−0.047	−2.537
$(\alpha^{int} outpeak \vert\ (\alpha^{int} out\&retpeak))^*\ s_4$	−0.054	−2.767
$\alpha^{int} retpeak^*\ s_4$	−0.050	−2.517
β_{TT}	**−0.013**	−4.037

The utility of departure from home for office commuters was higher before 9:00, while the utility of departure from work was higher after 17:00, compared to self-employed personnel. (Fig. 5 (b)). Such a scenario was also found in the trigonometric model. As mentioned, the usual office starting and closing times in Bangladesh are from 9:00 – 10:00 and 16:00 – 17:00, respectively. These periods are also known to be morning and evening peak hours. Schedule delay within these periods is expected to be minimum for the office employees, but with a greater possibility to get a late arrival penalty. Hence, to avoid the penalty of a late arrival in the morning and evening peak hours, office employees tend to prefer the other alternative periods to depart from home and work. For outbound trips of office commuters, the proposed model found the highest utility at 8:00 – 9:00; similarly, the highest utility in the trigonometric

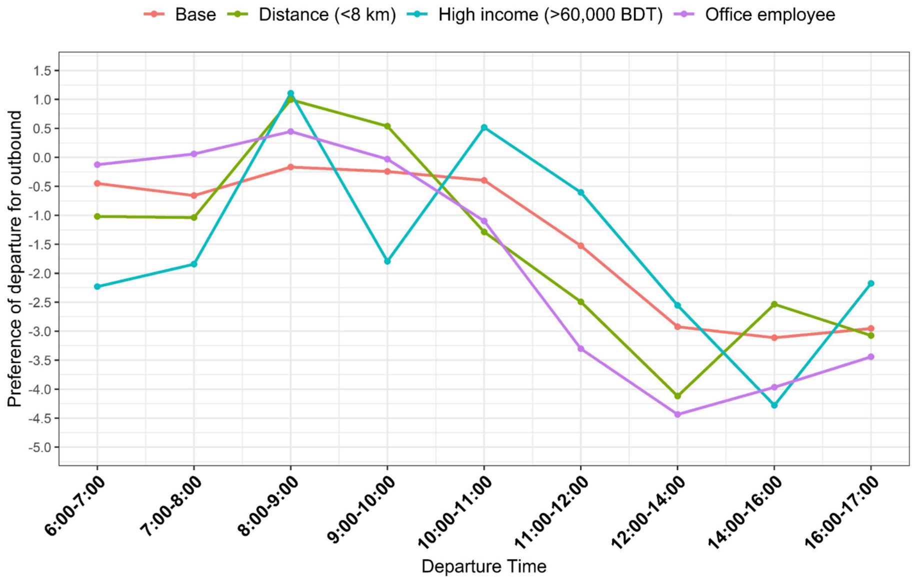


Fig. 4a. Intrinsic preference of departure time among different market shares following the trigonometric formulation while controlling travel time sensitivity (outbound).

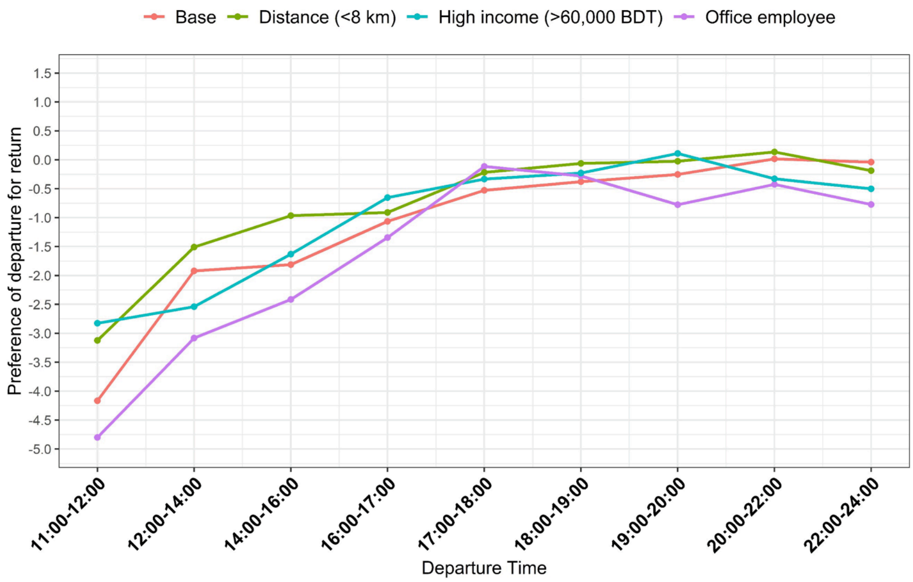
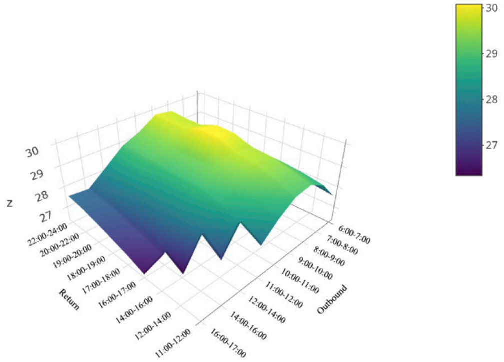


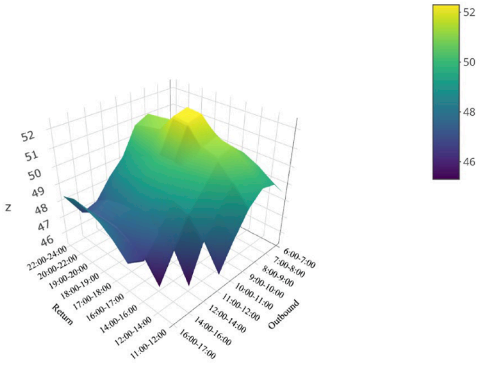
Fig. 4b. Intrinsic preference of departure time among different market shares following the trigonometric formulation while controlling travel time sensitivity (return). *These plots are prepared based on values of ASCs.

model was during 8:00 – 9:00. The observation data indicated that the highest percentage of office employees (car commuters) started their outbound journey at 8:00 – 9:00 (Fig. S1(a)). Additionally, results from the polynomial model revealed that the highest duration preference of office commuters was between 9 and 10 h, with the highest utilities for outbound and return journeys at 8:00 – 9:00 and 18:00 – 19:00, followed by 8:00 – 9:00 and 17:00 – 18:00, respectively. Since additional information about work flexibility and job type (full-time/part-time) was not available, no other additional experiment was carried out considering respondents' job types.

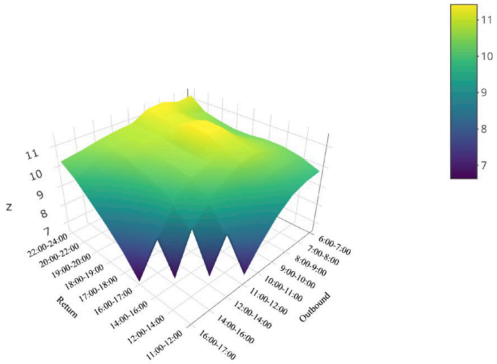
Furthermore, Fig. 5 (c) exhibits that short-distance travellers (<8km) were less likely to choose a limited number of alternatives compared to long-distance travellers. Though the intrinsic preference of departure time for outbound journeys of short-distance travellers was between 8:00 – 10:00, their departure time of return journeys was distributed from 17:00 to 24:00. Such a result from the proposed model agreed with the observed data (supplement Figure S1 (c and d)). Similarly, according to the state-of-the-art model, the distribution of departure time of car commuters for outbound was relatively skewered than the distribution for return. Hence, in Dhaka where major urban roads remain congested most of the time, congestion impacts on long-distance travellers are



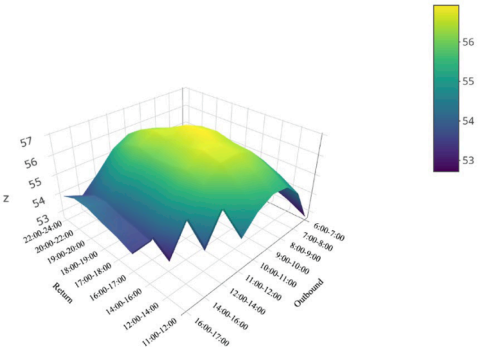
(a): Alternative specific constants for reference group
(highest utility at 9:00 – 10:00 to 18:00 – 19:00)



(b) Intrinsic preference of departure for office employee compared to the self-employed personnel
(highest utility at 8:00 –9:00 to 18:00 – 19:00)



(c) Intrinsic preference of departure for short distance commuters (<8km) compared to the long-distance commuters
(highest utility at 8:00 – 9:00 to 18:00 – 19:00)



(d) Intrinsic preference of departure for commuters from high income households compared to other income groups
(highest utility at 9:00 – 10:00 to 17:00 – 18:00)

Fig. 5. Heterogeneity in preference of departure time among different socio-demographic groups following the polynomial formulation while controlling travel time sensitivity. *These plots are prepared based on values of ASCs.

higher than the short distance travellers.

For car commuters from high-income groups (monthly income > 60,000 BDT), the utility of departure time for outbound and return journeys was the highest during the morning peak (9:00 – 10:00) and evening peak (17:00 – 18:00) compared to other alternatives (Fig. 5 (d)). A higher monthly income corresponds to a higher position in the corporate hierarchy, with less accountability for their actions. Therefore, such commuters are less likely to be affected by the consequences of a schedule delay and could prefer to travel during the peak time with a very minimal effect on their schedule. For the high-income commuters, the trigonometric formulation encountered an overfitting problem, predicting the highest utility of return trips between 19:00 and 20:00. However, the observation data indicated that a large share of high-income car commuters travelled between 17:00 – 18:00 (the supplement Figure S1 (f)).

5.3. Benefits of the proposed polynomial formulation over the state-of-the-art method

The previous departure time choice models attempted to address different methodological issues and provided functional approaches to handle the associated modelling complexities. This study introduced a new approach for modelling departure time choices that addresses the challenge of incorporating interaction parameters, rather than treating outbound, return, and duration as separate and independent dimensions. This study proposed a novel polynomial functional approximation that considers departure time, duration, and the correlation between these two dimensions. Results highlighted that interactions between departure time and duration play a crucial role in estimating time preferences. The model fit and prediction accuracy of the estimated models highlighted that the proposed integrated approach significantly improves the predictive accuracy of the model compared to the traditional approach of treating outbound, return, and duration as independent dimensions. Further, results revealed that the interaction parameters are significant in formulating the utility of different market shares such as office employees and high income (Table 7 (b)). It is noteworthy to mention that attempts to estimate the trigonometric model with interaction terms led to specification errors. This underscores the importance of the proposed functional approach in capturing correlations across different dimensions and their significance in predicting time-of-day preferences.

Besides, the proposed polynomial functional form is more flexible and requires fewer parameters compared to the state-of-the-art method. As a result, the proposed polynomial functional form is computationally less expensive and does not have complex identification issues. The results of the study reinforced the finding from the previous studies, which demonstrated the level of service attributes, trip attributes, and socio-demographic factors significantly influence time-of-day choice (Ben-Akiva and Abou-Zeid, 2013; Bwambale et al., 2019; Hess et al., 2005; Palma et al., 2021; Zannat et al., 2021). This study noted that missing information (e.g., preferred activity duration, preferred arrival or departure time) in RP data caused difficulties in estimating the time-of-day choice. In such a case, overlooking the correlation between departure time and duration could affect the role of critical explanatory variables (e.g., travel time). For example, in the proposed model the use of interaction terms in the estimation process enabled to capture the larger effect of different independent factors (travel time) and dimensions (departure time and duration) of the systematic utility while comparing to the sum of the individual dimension. Also, the model used functional approximation instead of a full set of constants for alternatives using RP data. Eventually, the novelty of the proposed functional form stands on its powerful capacity to capture the heterogeneity associated with the utility of departure from home at the same time but for different durations.

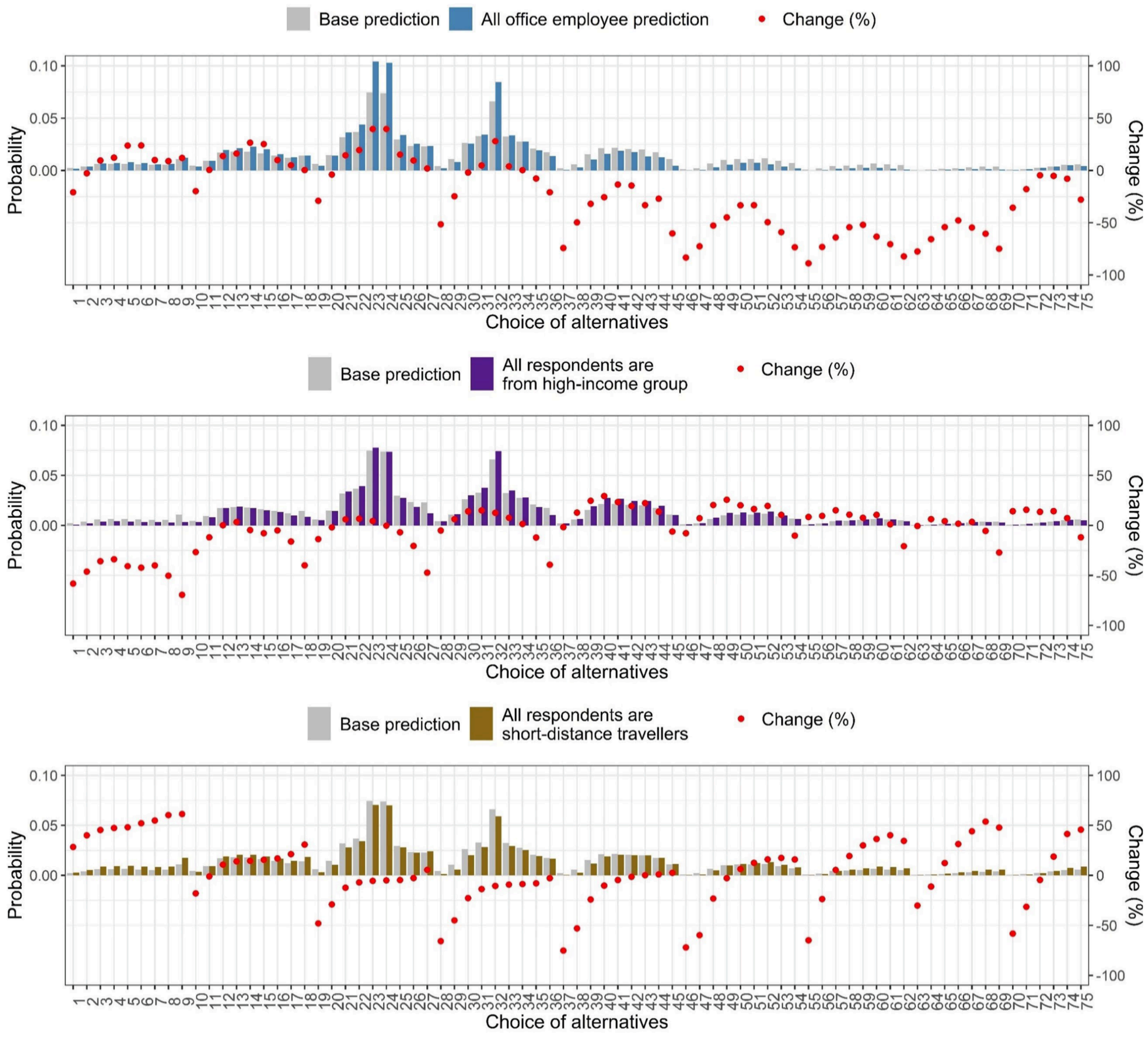


Fig. 6. Forecasting scenarios (details of choice of alternatives can be found it Table 3).

6. Policy insights

To address congestion issues such as congestion in peak time, various studies have emphasised the necessity for incentives (reduced fare for public transport, congestion tax for private vehicles) that encourage changes in transportation modes, destinations, and departure times (Kockelman and Kalmanje, 2005; Marshall and Banister, 2000; Moya-Gómez and García-Palomares, 2017). In Dhaka, where congestion reduction strategies are still in their infancy, primarily focusing on expanding capacity and encountering challenges during peak commuting hours, options such as relocating office locations or adopting remote work practices remain unpopular (Jamal et al., 2022). Additionally, other studies have demonstrated that car users exhibit strong resistance to mode switching due to factors like comfort and time sensitivity (Enam and Choudhury, 2011; Khan et al., 2011; Siddique et al., 2017). Given these constraints, adjusting departure times emerges as a viable option for mitigating peak-hour traffic congestion in major congested areas.

To gain insights into departure time preferences, it is crucial to employ a modelling framework capable of capturing the sensitivity to various aspects of time preference. In this article, we introduced a novel modelling framework that addresses a level of complexity that was previously unexplored in departure time choice modelling. The implications of our proposed framework and results can be understood in two distinct ways. Firstly, our findings highlighted a significant correlation between departure time and duration, shedding light on its importance in understanding time-of-day choices. This methodological contribution has the potential to enhance our comprehension of travellers' decision-making processes which can lead to a better policy intervention. Furthermore, the estimated model parameters have practical applications in formulating policies aimed at spreading peak-hour traffic to reduce congestion caused by car commuters in Dhaka, Bangladesh.

To highlight the practical application of the proposed model, we carried out 3 different forecasting exercises, each involving a modification of a specific attribute influencing the time-of-day choice, as considered within the model. In the first scenario, we assumed that everybody in the sample would behave as an office employee using a car for commuting. In the second scenario, it was assumed everyone in the sample would be short-distance car traveller and in the third scenario everyone would be from a high-income household. The summary of the forecasting is summarised in Fig. 6. For each scenario, we presented the forecasted average probability for each time choice, along with the percentage change from the base scenario. The base prediction presented the choice context replicated by the proposed model and this prediction served as initial reference point for the forecasting. Furthermore, we presented in Table S1 the proportion of the sample that selected each alternative, in conjunction with the base prediction providing a validation of the model. In the first scenario (all car commuters office employee), a discernible rise in the likelihood of choosing morning and afternoon peaks, as opposed to other off-peak time periods, was observed. This shift was accompanied by a reduction of time choice during off-peak hours. A similar increase in peak-hour travel demand was observed when examining an increase in respondents from high-income households. However, their likelihood of shifting towards the peak hour was relatively lower compared to office employees. For these socio-demographic groups, the correlation between departure time and duration exerted a significant and dominant influence on the choice of earlier times of the day (around the time of morning and afternoon peak), especially when there was a longer duration requirement. In scenario 2, where a correlation between departure and duration was lacking, substantial shifts were noted during the morning and evening off-peaks.

Based on our results and forecasting analysis, we outline different proposals for our case study (Table 8):

7. Conclusions

This study presented a novel polynomial approximation of alternative specific constants (ASCs) to model departure time choice. The proposed functional form captured the interaction among different dimensions of time preference such as outbound, return, and duration. To the best of our knowledge, this was the first attempt to investigate the correlation between departure and duration within a departure time choice model framework. A joint departure time choice model (outbound and return) of car commuters was developed based on RP data from Dhaka, Bangladesh. The results indicated that the choices were significantly affected by the travel times and socio-demographic profile of the respondents. The proposed model reasonably agreed with the observed pattern.

The current study can be extended in several directions in the future. Firstly, the scope of this study was exclusively on car commuters. In the future research, it is crucial to apply our proposed modelling framework across various mode users and trip purposes. Such investigation will help examine the presence or absence of correlation in their time-of-day choice. Further, a similar structure can provide additional insights about non commute trips as well. It may be noted that the departure time choice for non-commute trips is more complex as there may be more flexibility associated with the choice of activity destination and mode. In such cases potentially warranting a joint model for departure time, destination, and mode. Our proposed polynomial functional form will serve as a foundational starting point for developing models that address the complexity of joint choice scenarios, accommodating multiple correlations across various activity and travel dimensions. Secondly, a lack of observed data post-implementation of strategies aimed at shifting time-of-day choices hinders the testing of the prediction accuracy of the proposed model. It is worth noting that, as of now, Dhaka has not implemented strategies such as congestion pricing, flexible working hours, time variant fares, etc. that could provide relevant data for such testing. In the future, after the implementation of any peak-spreading policies, the temporal preferences of car commuters can be compared with observed data, following the approach proposed by West et al. (2016) and Eliasson et al. (2013), to assess the accuracy and effectiveness of the proposed model's predictions. Thirdly, this study ignored the potential correlation between adjacent departure times to retain simplicity for practical implication. Future research can focus on estimating correlations of alternatives by using a more complex modelling framework, such as a cross-nested logit model or mixed MNL model, to account for the correlation among the alternatives. Finally, the current departure time choice model can be linked to a network assignment model specific to car users to evaluate potential route choice under dynamic traffic situation. Also, the research findings

Table 8
Significance of direct model output to formulate peak-spreading policies targeting car commuters.

Estimated parameters	Outcomes	Policy implication
Correlation between departure time and duration (activity and travel combined)	We found a negative correlation between departure time and duration, indicating that long duration requirements led to a preference for earlier departure times.	To meet the needs of car commuters with requirements of longer durations, it is essential to recognise that they often need to begin their journeys early in the morning. particularly in morning peaks, to ensure they have enough time to meet their workplace requirements within standard opening and closing hours. We observed that a significant portion of car commuters, approximately 46 % of the respondents we selected, fall into this category, requiring a duration window of more than 8 h.To alleviate the demand during the morning rush hour for those who need to travel early for longer durations, it is vital to introduce flexibility in work hours and office starting times, whenever possible. This approach strengthens the findings of a study by Kockelman and Kalmanje (2005), which highlighted that congestion pricing policies face challenges when fixed office hour requirements are in place.
Time dependent correlation	During the morning and evening peak hours, the correlation between departure time and duration appeared to be relatively weak compared to other time periods.	Results highlighted that there was a weaker association between departure time and duration during peak hours. This implies that at the morning and evening peak, the need for a longer duration had less impact on encouraging people to opt for an earlier departure before the peak hours. The potential reason can be the disutility of arriving early or late at work (De Palma et al., 1990; Hendrickson and Plank, 1984). To complement this, peak spreading policies could promote off-peak travel by offering pricing incentives for travelling before or after peak hours. Additionally, implementing flexible work schedules, such as starting work before or after the usual office hours, can further mitigate the impact of early arrival waiting time.
Effects of occupation type (office employees vs. self-employed personnel)	Outbound and return office employees preferred morning and evening peak with a longer duration requirement. Also, the forecasting analysis shows that if there were an increase in car commuter office employees, there would be a shift from other off-peak alternatives to peak periods.	The significant difference between the office employees and self-employed individuals highlighted the fixed work hours and strong schedule delay effect on office employees. This served as indirect evidence that the introduction of staggered work hours or teleworking options could motivate office employees to travel during the off-peak hours.
Effects of distance (short vs long distance)	The preference of short-distance travellers exhibited a more distributed patterns of departure times across different time-of-the-day, compared to long-distance travellers. Moreover, the forecasting analysis shows a major shift of short distance car travellers towards off-peak hours as the number of short-distance travellers increased.	These findings suggest that policies aimed at managing congestion and optimising transportation resources may need to vary based on travel distance. For short-distance car travellers, strategies should focus on reducing travel time during off-peak hours and providing incentives to encourage off-peak travel, thus shifting demand away from peak periods. For long-distance travellers, it may be beneficial to implement strategies to reduce the need for longer car travel (such as park-and-ride facilities) (Marshall and Banister, 2000) or encourage teleworking and help spread out their departure times to reduce congestion during peak hours.
Effect of Income	Significant differences in correlations between departure times and durations among different income groups were found. Like the office employee, an increase in respondents from high-income households would result in higher demand around peak times.	High-income car commuters were more likely to choose peak travel times. This group has higher affordability and is less likely to be price sensitive. This result complied with the findings from the study by Kockelman and Kalmanje (2005) in the context of global south.
Sensitivity to travel time	Increase in travel time negatively impacted the utility (i.e., travellers prefer shorter travel times over longer ones) of car commuters.	To motivate car commuters to avoid peak hours and choose different times, it is important that travel during off-peak hours is consistently faster. If there is hardly any difference in travel times between peak and off-peak hours, it will become challenging to encourage people to explore other alternative times of the day as potential alternatives. In such cases, intervention to change departure time may not be an effective congestion management strategy.

can be implemented in an agent-based simulation platform to take into account the interaction of car users with other mode users and test the impact of different peak spreading or congestion pricing policies.

Nevertheless, the proposed functional form overcame several issues related to the time preference model. As such, the proposed model (1) did not have the overfitting problem and gave more behaviourally realistic outputs, (2) reduced the computational cost by reducing the number of constants required to model time preference with the full set of constants, (3) addressed the issues associated with the correlation between departure time and the activity duration, (4) could accommodate multiple peaks without a priori assumption, and (5) had the potentiality to fit with both RP and SP data. The findings can be practically useful for devising peak-spreading policies for car commuters in Dhaka — either as a stand-alone tool to test the impact of varied start times of offices in different locations or within an agent-based simulation tool to test the impact of different congestion reduction demand management policies.

CRediT authorship contribution statement

Khatun E. Zannat: Writing – review & editing, Writing – original draft, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Charisma F. Choudhury:** Writing – review & editing, Supervision, Funding acquisition, Data curation, Conceptualization. **Stephane Hess:** Writing – review & editing, Supervision, Software, Methodology.

Declaration of competing 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.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.tra.2024.104081.

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