# Understanding transport mode choice for commuting: The role of Affect

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**Abstract**

This study examines the relationship between positive and negative user valence and transport mode choice behaviour. We integrate latent attitudes ‘affect’ and ‘salience’ into transport mode choice models using the framework of integrated choice and latent variable modelling and simultaneous maximum likelihood estimation methods. The results are consistent with findings in similar travel behaviour and behavioural economics literature. The study extends the findings of previous research and has demonstrated that user sentiments about public transport mode and salient public transport experiences have a significant impact on travel mode choice behaviour. It was found that private motorised users are more sensitive to overcrowding and antisocial behaviours on PT than active and PT travellers. Key attitudinal indicators influencing individual transport choice behaviour are established to guide public policy. The key indicators of Affect and Salience must be analysed and addressed through public policy to enhance PT user experience and develop services and facilities to increase the utility of PT in-vehicle travel time.

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## 1 Introduction

Our knowledge of rational decision-making is incomplete without the appreciation of the role of emotion in human decision-making (Simon, 1982). Emotion is a conscious positive or negative reaction to an event whiles "Affect" describes an automatic response to a good or bad experience (Baumeister and Bushman, 2014). Several studies have investigated the impact of emotion on human information processing, particularly in decision-making and concluded that negative experiences can impair decision-making and influence behaviour (Damasio, 1994; Elster, 1998; Loewenstein, 2000; Naqvi, Shiv and Bechara, 2006; Resnick, 2012). Elster (1998) confirmed the findings of Damasio and further espoused that social norms were promoted and sustained by emotions; emotions serve as the intermediary between situation and behaviour and, are essential for behavioural adaptation and survival (Scherer, 2005; Dewall et al., 2016). It is common knowledge that fear leads to flight while anger results in action, even when reactions could sometimes be against one's economic interest (Loewenstein, 2000; Scherer, 2005).

Kahneman (2013) explained that intense emotional arousal temporarily overrides cognitive faculties or what the author calls "system two". This could serve as a functional equivalent to the suspended rational function in such circumstances swaying the perception of utility more towards emotional satisfaction rather than economic utility (Elster, 1998). The evidence above and the recent latent and hybrid choice models motivate this study. The study seeks to investigate the impact of emotional attachment on the intraurban travel behaviour of the residents of Edinburgh. The novelty of this study is the incorporation of Affect and Salience in Integration choice and latent variable (ICLV) model and the definition of key indicators underlying Affect and Salience, which drive individual choice preference beyond the traditional objective and socio-demographic variables.

The paper is structured as follows: the first two sections introduce the study and presents the review of relevant literature. The third section presents the methodology and the framework adopted for the study, section four covers the descriptive analysis of the sample data followed by section five on model estimation and finally, section six presents the discussions and conclusion of the study.

## 2 Literature Review

Baumeister & Bushman (2014) defined emotion as a "conscious state that includes an evaluative reaction to an event and Affect as an automatic response to a good or bad experience". Affect could have a transient or lasting effect on the decision-maker and can consciously or unconsciously influence behaviour (Champney and Stanney, 2007; Davidson, Sherer and Goldsmith, 2009).

Sentiment is a form as Affect and describes an emotion a subject directly attaches to a tangible target as a result of the subject interaction with a target object. This type of Affect is categorised either as positive valence (joy, satisfaction, pleasure) or negative valence (shame, embarrassment, anger, fear, frustration) (Resnick, 2012). Sentiments, if intense, would usually emerge whenever the subject is dealing with the target in question. Similarly, we believe that any sentiment associated to a travel mode could potentially affect behaviour towards that mode, most importantly when the emotion provoked is intensely negative (Liz, Joyce and Mick Smith, 2016). Sentiments can be remarkably influential and can overrule otherwise rational course of action even in the presence of cognitive information that would suggest alternative courses of action (Loewenstein, 2000; Loewenstein et al., 2001). Rozin, Millman and Nemeroff (1986) suggested that once a consumer attaches emotion to a decision targets, it influences the desirability of the target and become difficult to detach. Consumer's experiences with a particular product or service could create temporal or lasting emotional attachment or detachment towards the products or service, which could influence behaviour (Liz, Joyce and Mick Smith, 2016). Ariely (2008) submits that Affect offers a possible explanation for consumer judgments, such as the zero price effect on consumers.

In transport, the rational choice theory suggests that the decision-makers evaluate the economic satisfaction of their choice set and select the mode with the highest economic satisfaction (Ben-Akiva and Lerman, 1985). However, Elster, suggested that aside from the economic satisfaction, decision-makers also evaluate their choice sets emotionally. If the perceived emotional satisfaction or psychic benefit of one product is found higher than the economic satisfaction of using alternate product then subject to economic limitations, the decision-maker will select the choice with the highest emotional satisfaction, contrary to logic (Zajonc, 1980; Metcalfe and Dolan, 2012; Elster, 1998; Loewenstein, 2000). Elster (1998) investigated the role of emotion in decision making when rationality alone appears insufficient to explain a phenomenon and consequently proposed for emotion to be treated as psychic cost in a utility function similar to other cost variables. Loewenstein (2000) further proposed the incorporation of emotions into the rational choice theory unless the predicted behaviour is less influenced by emotional factors. A traveller might prefer using a particular mode of travel for several reasons, including economic and environmental. However, any negative emotional encounter with such travel mode could have an incredible impact on the traveller's loyalty to the mode.

Morris and Guerra (2015) investigated the effect of trip duration during travel on travellers' emotion by comparing commuter satisfaction across three modes of transportation Car, Non-motorised transport (NMT) and Public transportation (PT). The researcher found that long commuting trips significantly impact travellers emotionally and degrade the mood of commuters.

Similarly, research in behavioural science suggests that the human memory of experiences is governed by the most intense' peak' moments and final impressions in a chain of events (Kahneman, 2013). Information that stands out and seems relevant affect human decision-making (Dolan et al., 2010).

Human behaviour is believed to be influenced by what comes to mind when options are being evaluated for decision making. Salience describes such intense, unusual, extreme or unexpected user experiences. It is proposed that any prominent (desirable or undesirable) user experience with a travel mode can have a disproportionate influence on behaviour. For instance, any encounter of provocation experienced by a passenger on a bus could have a profound consequence on their future travel behaviour (Kahneman, 2013). Resnick (2012) explains that such undesirable experiences create negative valence and could negatively reshape the subject's future travel decisions (Metcalfe and Dolan, 2012b). Therefore, based on the above evidence, we hypothesise that traveller's emotional attachment to travel modes, and undesirable experiences could influence their travel behaviour.

The last two decades have witnessed a rising research interest in latent or integrated choice and latent variable (ICLV) modelling, in direct response to the observed limitations of the traditional choice models in explaining the observed heterogeneity of human behaviour and individual choice preferences (Ben-Akiva and Boccara, 1995). Literature is replete with evidence suggesting that attitudes and perceptions significantly influence decision-making (Manski, 1973; Ben-Akiva and Boccara, 1995; Ben-akiva *et al.*, 2002; Ortuzar *et al.*, 2011; Kamargianni *et al.*, 2015). The challenge, however, is finding the appropriate subjective variable to account for in the choice models.

This study leverages on the strength of the argument advanced above for Affect and Salience. It incorporates them as latent variables to develop an ICLV model to investigate their impact on travel mode choice.

# 3 Methodology

## 3.1 Respondents

The target population of the study was residents living within the jurisdiction of the City of Edinburgh council area aged 18 years and above. The sampling frame of the survey comprised of 240,147 households stratified into 20 zones based on the 2016 Scottish Index of Multiple Deprivation (SIMD) classification (Scottish Government, 2016). The SIMD postcode lookup table is an area-based tool for identifying areas with similar socio-demographic characteristics. It uses information such as income, education and crime levels to assign scores to data zones and postcodes (Campbell *et al.*, 2020; Scottish Government, 2016). The SIMD postcode lookup table was used to classify the sample frame into socio-economic zones for sampling and to ensure a proportional and representative sample. Households were drawn at random from each zone (stratum) to generate the sample. The number of addresses drawn from each stratum was based on its respective weighting in the sampling frame to ensure proportional representation of the sample. 4,155 household addresses were sampled for the study, out of which 3,973 addresses were successfully accesed and delivered a questionnaire to complete and return by mail to the researcher using a Printed Postage Impressions (PPIs) enclosed with the questionnaire.

## 3.2 Questionnaire design

The survey instrument was designed to collect socio-demographic data, transport characteristics and information for attitudinal profiling (Affect, Salience, Norms and Narcissism) for intraurban trips . The first section of the questionnaire sought information on trip and travel characteristics including the main mode of travel and secondary mode of travel in the absence of the main mode. The second section covers user perception of PT service quality (Affect), PT user experience and its effects (Salience), user perception on transport and environmental norms of the study area (Norms) and statements on Narcissistic Personality Inventory (NPI) for estimating repondents' NPI score (Narcissism); These measurement scales were measured on a five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). However, this study only investigates the impact of Affect (measured with 6 indicators) and Salience (measured with 8 indicators). The final section of the survey instrument asked for information necessary to understand the socio-demographics of the sample, questions such as gender, age, marital status, highest education qualifications, annual household income, employment status and household size were asked. This information is used in conjunction with other relevant variables to investigate the travel behaviour of the study population.

## 4 Sample characteristics

### 4.1 Socio-demographic

In total, 551 completed questionnaires were received from respondents aged between 18 and 90 ($\mu$=49.69, $\sigma$=17.45). Fifty-one partially completed responses were discarded from the sample data. This reduced the total valid responses to 500 cases at a response rate of 12.6%. Although the response rate is consistent with postal or mail back survey (David De Vaus, 2002; Sahlqvist *et al.*, 2011; Larson and Poist, 2018), it is below the study's expectation of 17%. The researchers suspect that the sensitivity of some of the indicators for measuring the attitudinal constructs may have influenced the non-response. All respondents met the minimum legal age of 17 for obtaining a driver's licence in the UK. It was observed that 82.8% of respondents own either full or provisional driving licence. 13.5% have never held a licence, 3.4% have surrendered their licence and none was disqualified from driving. This indicates that at least 96.3% of respondents are legally eligible to own a car and drive in the study areaThe next section presents a descriptive analysis of the sample data.

Table 1 reports the characteristics of the study population and indicates that there are fewer males than females in the sample. A total of 349 participants, representing 69.2% of respondents reported having at least one car available for commuting. This statistic is slightly different from similar figures from Transport Scotland (Transport Scotland (2018b). However, a chi-square test conducted ($x^2$= 1.916 at a p-value of 0.853) suggested both data sets come from the same population; thus, the data set is representative of the study population. A comparison of the estimates on car ownership was insignificant with a chi-square value of 1.19 at a p-value of 0.756 (Transport Scotland, 2018b). Similarly, it was found that 35% of participants commute by driving, while 32% of them reported taking the bus or tram. The sample data was found not to significantly differ from similar data from Transport Scotland (Transport Scotland, 2018a). The study further investigated the household income of participants and compared the sample data with similar records from the Scottish Government (Scottish Government, 2018) ($x^2$= 2.737 at a p-value of 0.603). The sample estimates on education show a high proportion (62.7%) of respondents with at least first degree. Although the distribution of the population by educational attainment could not be sourced and compared with the sample data, CoEC (2018) indicates that 63.9% of Edinburgh's population in employment have a university degree. Again this estimate does not deviate much from the sample data. We, therefore, assume that the two datasets belong to the same population and do not differ statistically.

### 4.2 Attitudinal variables

We investigate the effect of respondent's perception, experience and emotions about PT on their choice of travel mode for commuting. The study aims to examine any significant difference in attitude between PT users, private car users and active travellers (Non-Motorised Transport (NMT)). As indicated previously, we measured the attitudinal dataset on a 5-point ordinal scale. For this reason, we employed the Kruskal–Wallis Test to assess the differences among the three groups of commuters statistically. The Kruskal-Wallis test is the nonparametric version of the one-way ANOVA. It is an extension of the two-group Mann-Whitney U (Wilcoxon rank) test and more generalized form of the Mann-Whitney U test (McKight and Najab, 2010).

Table 1: Sample characteristics

| Characteristics | | Statistics |
|---|---|---|
| 1 | Gender | Male (47.6%), female (52.4%) |
| 2 | Age | 18-24 (6.0%), 25-34 (15.7%), 35-44 (13.7%), 45-54 (18.4%), 55-64 (20.9%), 65-74 (15.9%), >75 (9.3%) |
| 3 | Income | <10,000 (10.6%), 10,000-20,000 (19.5%), 20,000-30,000 (20.9), 30,000-50,000 (22.9%), >50,000 (27.1%) |
| 4 | Car Ownership | No car (30.2%), 1 car (49.7%), 2 cars (16.4%), 3+ cars (3.7%) |
| 5 | Modal share | Walking (18.9%), Cycling (8.2%), Car/van as driver (35.1%), Car/van as passenger (3.9%), Bus/Tram *32.1%), Rail (1.3%), Taxi (0.4%) |
| 6 | Household size | One (32.8%), two (41.0%), three (12.0%), four (14.0%), five or more (0.2%) |
| 7 | Qualification | No formal education (1.24%), High school (16.8%), College (19.3%), First Degree (33.5%), Masters Degree (23.5%) and PhD (5.6%) |
| 8 | Employment status | Full time (44.7%), Part time (16.15%), Student (6.0), Retired (30.2%), Unemployed (2.9%) |

**Affect**

Respondents were requested to indicate the extent to which they agree or disagree with the statements in table 2. Kruskal–Wallis Test was used to establish the similarities or otherwise in Affect between respondents commuting by NMT, Car and by PT. It can be seen from Table 2 that respondents differ significantly in *Affect* between the three groups. As can be seen three out of the six variables statistically vary considerably between the three groups at 99% confidence level; two statistically differ at 95% confidence level, and only one variable is not statistically different. In general, we assert that the measurement instrument for *Affect* statistically explains the difference in respondents' choice of transport mode for commuting.

Table 2: Difference in Affect between NMT, car and PT users

| Variable | Mean | Std Deviation | Kruskal–Wallis Test | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | | Mean Rank | | | Chi-Square | Sig | |
| | | | Car (N=190) | PT (N=175) | NMT (N=131) | | | |
| I enjoy using PT ... I get to meet people | 2.12 | 1.047 | 239.18 | 272.57 | 226.21 | 9.778 | 0.008 | *** |
| Travelling in PT is boring | 2.45 | 0.966 | 242.59 | 245.68 | 253.30 | 0.515 | 0.773 | |
| I can use travel time for other activities | 3.34 | 1.004 | 206.85 | 279.03 | 270.35 | 30.335 | 0.000 | *** |
| Driving is demanding | 3.45 | 1.164 | 220.17 | 277.12 | 253.47 | 15.795 | 0.000 | *** |
| I use PT for the Environment | 3.24 | 1.166 | 221.52 | 260.06 | 274.28 | 12.901 | 0.002 | *** |
| Uncomfortable travelling with strangers | 2.05 | 1.101 | 271.47 | 233.48 | 231.55 | 9.734 | 0.008 | *** |

***: p<0.1, **: p<0.050, ***: p<0.01**

We observed that PT users show more affinity to PT services than car and NMT users and are more likely to rate PT services more favourably. PT and NMT commuters consider driving as demanding and believe the in-vehicle travel time of PT could be utilised for productive activities. We further observed that drivers are less sensitive to the environmental impact of their travel behaviour. NMT and PT users, on the other hand, appear more environmentally conscious and more likely to prefer PT to driving. Perhaps sensitisation from environmentalist may be necessary to address this perception gap. While PT and NMT users do not have difficulty sharing seats with strangers in PT, Car users were found to be less enthused about travelling and possibly sharing a seat with strangers in PT travel modes. This is perhaps one of the several reasons behind the choice of private motorised mode for commuting. The results indicate that active commuters and PT commuters are more likely to be satisfied with PT services than drivers. It is also shown that the level of satisfaction varies considerably by mode.

**Public Transport Experience**

Respondents were asked to indicate the extent to which the experiences in the table below would affect or have affected their usage of the public bus. Kruskal–Wallis Test conducted on this measurement tool is shown in Table 3. As can be seen, respondents differ significantly in response across the three groups. Three variables statistically differ between the two groups at 99% confidence level; one statistically differs at 95% confidence level, whiles four of the variables differ at 90%.

Table 3: PT Experience between NMT, Car and PT users

| Variable | Mean | Std Deviation | Kruskal–Wallis Test | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | | Mean Rank | | | Chi-Square | Sig | |
| | | | Car (N=186) | PT (N=168) | NMT (N=129) | | | |
| Anti-social behavior | 3.21 | 1.412 | 272.85 | 219.49 | 233.84 | 14.366 | 0.001 | *** |
| Overcrowding | 3.13 | 1.258 | 255.36 | 223.85 | 246.32 | 4.915 | 0.086 | * |
| Exposure to health risk | 2.67 | 1.322 | 259.28 | 232.12 | 226.29 | 5.617 | 0.060 | * |
| Passenger Annoyance and discomfort | 2.95 | 1.190 | 262.40 | 213.51 | 240.83 | 11.634 | 0.003 | *** |
| Poor hygiene (uncleanliness and smell on bus) | 3.36 | 1.288 | 262.99 | 220.16 | 243.94 | 8.740 | 0.013 | ** |
| Inaccurate bus and real-time information | 3.08 | 1.252 | 255.56 | 224.57 | 246.91 | 4.754 | 0.093 | * |
| Long waiting and travel time | 3.39 | 1.327 | 254.25 | 221.08 | 247.78 | 5.698 | 0.058 | * |
| Safety issues (seatbelts, toilets etc.) | 2.33 | 1.287 | 246.10 | 225.65 | 247.82 | 2.734 | 0.255 | |

***: p<0.1, **: p<0.05, ***: p<0.01**

Comparing the three groups (Drivers, NMT and PT users), Table 3 indicates that in general, drivers and then followed by NMT users will have their loyalty to PT significantly influenced by negative passenger attitude and negative user experiences on PT. In general, drivers are more sensitive to negative and undesirable experiences associated with PT usage; they are more likely to be influenced by such these and similar experiences than PT users followed by active travellers.

## 5 Mode Choice Modelling

### 5.1 Maximum Likelihood factor Analysis

Maximum likelihood (ML) factor analysis with Promax rotation was undertaken to extract uncorrected attitudinal constructs using SPSS. Maximum likelihood estimator is adopted because of its robustness in handling ordinal and normally distributed data (Dannewald *et al.*, 2008; Muthén and Muthén, 2010). The factors were constructed using 11 out of the 14 statements used for measuring *Affect* and PT experiences with 500 valid responses. Three indicators: *"I am uncomfortable travelling with strangers";* "*Travelling in PT is boring"* and *"I enjoy using PT ... I get to meet people"* had communalities below 0.2 and were consequently omitted from the analysis (Child, 2006; Yong and Pearce, 2013).
Using the scree plot, three factors explaining 65.49% of the variance were retained. The first factor, named *"salient experience" (salience)* accounts for 40.73% of the variance and describes participants' perception of negative experience on public transport (bus services in Edinburgh). The second factor, *"Convenience*", accounts for 16.40% of the variance. This factor describes how respondents' see the travel and waiting time of public transport services. The third factor, *"Affect*" (PT Lovers) also accounts for 8.36% of the variance and describes respondents' perception of Bus/Tram travel and the act of driving*. Table 4* shows the results of the factor analysis and Cronbach's Alpha test of construct reliability (Cronbach, 1951).

Table 4: Factor Analysis

| Factor Analysis | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Variables** | | **Mean** | **SD** | **Factor** | | |
| | | | | **Salient experience (40.73%)** [a] | **Convenience (16.40%)**[a] | **Affect (8.36%)**[a] |
| Variable [b] | Cronbach's Alpha | | | 0.855 | 0.835 | 0.701 |
| Sal_4 | Passenger Annoyance and discomfort | 2.8 | 1.390 | 0.855 | | |
| Sal_3 | Exposure to health risk | 2.6 | 1.456 | 0.794 | | |
| Sal_1 | Anti-social behaviour | 3.2 | 1.514 | 0.735 | | |
| Sal_2 | Overcrowding | 3.0 | 1.412 | 0.618 | | |
| Sal_5 | Poor hygiene (uncleanliness and smell on bus) | 3.3 | 1.428 | 0.488 | 0.364 | |
| Sal_8 | Safety issues (seatbelts, toilets etc.) | 2.2 | 1.422 | 0.353 | | |
| Sal_7 | Long waiting and travel time | 3.3 | 1.511 | | 0.97 | |
| Sal_6 | Inaccurate bus and real-time information | 3.0 | 1.391 | | 0.629 | |
| Aff_4 | Driving is demanding | 3.5 | 1.167 | | | 0.823 |
| Aff_3 | I can use the travel time in PT for other activities | 3.3 | 1.005 | | | 0.571 |
| Aff_5 | I use PT for the Environment | 3.2 | 1.165 | | | 0.547 |

**[a] Percentage of variance explained, [b] variables used in the analysis**

Latent class analysis of the latent factors together with personal/household characteristics of the respondents (i.e. age, employment status, gender, education, household income and car ownership) was carried out to examine any possible distinct attributes differentiating the respondents in latent factors in table 4. The latent class analysis suggests that respondents belonging to and scoring high on the latent construct, Affect, are most likely to be people aged 45 years and above and in fulltime employment (54%). Members in this category mostly travel by PT (67%) or NMT (25%) while 51% of respondents in this class do not own or have a car available. This possibly explains why they show positive valence towards the PT and have high disutility for the private motorised mode.

Similarly, respondents belonging to and scoring high on the latent construct salient experience (salience) were found to be mostly women (61%), majority of them own at least one car (74%). A higher proportion of respondents in this class often drive (46%) compared to using PT or active modes. 59% of members in this category own Lothian bus travel pass (ridacard) or another travel pass, a possible indication of active or loyal PT users whiles, 41% of the class members do not own any form of travel pass.

## 5.2 Confirmatory Factor Analysis

Using AMOS Structural Equation Modelling (SEM) package, we performed a confirmatory factor analysis (CFA) to validate the factors extracted using the maximum likelihood factor analysis. The CFA factors are used as the latent variables in the estimation of ICLV model. Dobbie, McConvile and Ormston (2010) found that overcrowding, walking distance to bus stops and lack of toilets on board buses are among the barriers to PT usage in Scotland. The sample data buttresses this claim and indicates that 18.4% of respondents are concerned about the absence of seatbelts and toilets. However, the indicator "Safety issues (seatbelts, toilets)" was found to have very low factor loading during the CFA and was consequently dropped from the final CFA model. All the factors achieved composite reliability (CR) (i.e. CR>0.69) and therefore considered reliable (Hu and Bentler, 1999). Similarly, all the latent factors except Affect achieved convergent validity (i.e. average value extracted, AVE >0.50) (Hu and Bentler, 1999). However, Malhotra and Dash (2011) suggest that due to the strictness of AVE, reliability can be assumed if a factor achieves CR. Therefore, following the advice of Malhotra and Dash, reliability is deemed established for all the factors. The assessment of discriminant (divergent) validity (the degree to which two conceptually similar concepts are distinct) found a high correlation between Salience and Convenience (square root of the AVE for salience is less than its correlation with Convenience). Thus, Salience and Convenience did not achieve discriminant validity(Hu and Bentler, 1999; Kline, 2011). Convenience was, therefore, dropped from subsequent analysis as a result and due to the focus of the study. The final model satisfied all indices recommended for assessing goodness-of-fit (see Hu and Bentler, 1999; Kline, 2011), indicating that the measurement model sufficiently fits the sample data. Table 5 below presents the results of the CFA.

**Table 5: CFA Model**

| CFA validity and reliability | | | | |
|---|---|---|---|---|
| Factor | **CR** | **AVE** | **MSV** | **MaxR(H)** |
| Salience | 0.853 | 0.538 | 0.658 | 0.865 |
| Convenience | 0.808 | 0.678 | 0.658 | 0.813 |
| Affect | 0.708 | 0.458* | 0.026 | 0.787 |
| CFA Fitness Indices | | | | |
| **Measure** | **Estimate** | **Threshold** | | |
| CMIN | 72.673 | | | |
| DF | 29 | | | |
| CMIN/DF | 2.506 | <3.0 | | |
| CFI | 0.977 | >0.90 | | |
| NFI | 0.963 | >0.90 | | |
| TLI | 0.964 | >0.90 | | |
| SRMR | 0.032 | <0.08 | | |
| RMSEA | 0.055 | <0.06 | | |
| PClose | 0.278 | >0.05 | | |

**CR: Composite reliability; AVE: Average value extracted; MSV: Maximum shared variance; MaxR(H): McDonald Construct Reliability**

### 5.3 Model Specification

The model estimation uses the simultaneous estimation method in Pandas Biogeme (Bierlaire, 2018a; Bierlaire, 2018b). We estimate an integrated choice and latent variable model (ICLV model). We further estimated a logit model with similar specifications as the ICLV model but without the latent attitudes as a reference model. The reference model (base model) is used to evaluate the integrated choice model for any added value or otherwise.

The framework for the ICLV model is illustrated in Figure 1. It consists of two components: a discrete choice sub-model and a latent variable sub-model. The factors extracted during the factor analysis and CFA are used as latent variables in addition to the observed socio-demographic variables.

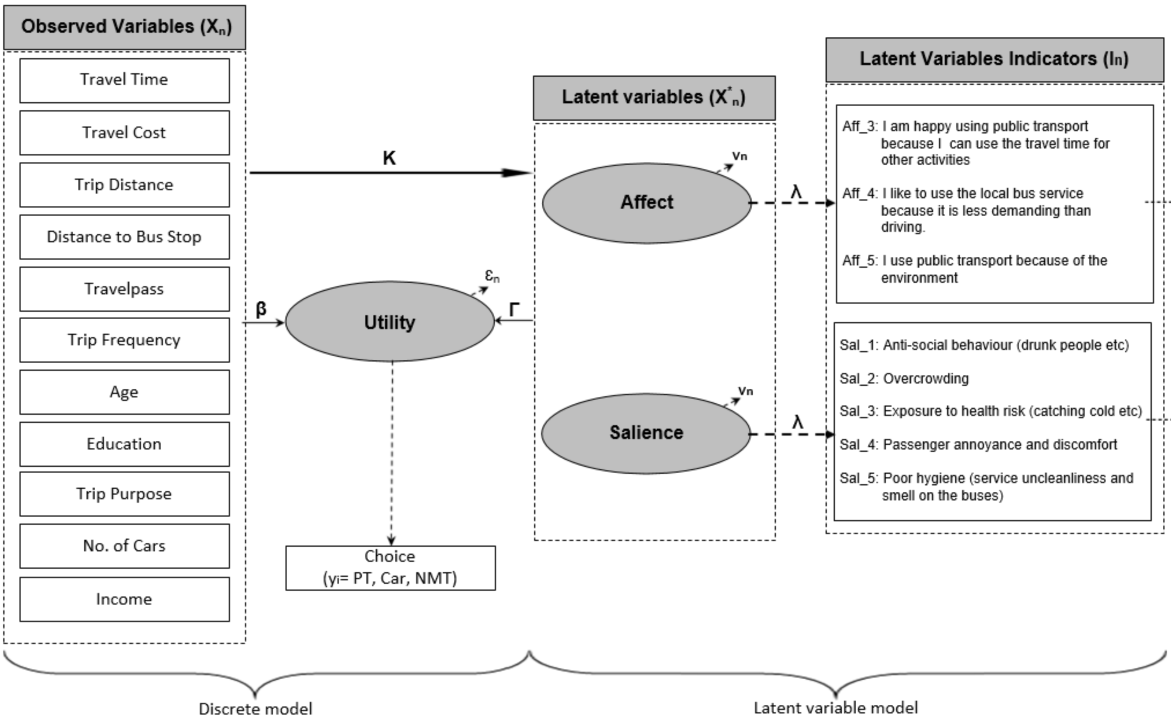

Figure 1: Mode choice model

**Latent Variable Sub-model**

The latent variable sub-model consists of a measurement model and a structural model. The indicators for the latent attitudes "PTLovers" and "Salience" as shown in Figure 1 are used for the specification of the measurement model. The Measurement equations were built with the respective indicators of the latent attitudes using equation (1) (Ben-Akiva and Boccara, 1995; Ben-Akiva *et al.*, 1999; Bierlaire, 2018a).

$$I_n = \alpha_n + \lambda_n X_n^* + \eta_n\,, \quad \forall n, \eta_n \sim N(0, \textstyle\sum_{\eta_n}) \tag{1}$$

Where:

$I_n$: is a vector of indicators of the latent attitude

$X_n^*$: is the latent attitude (Affect/PT Lovers and Salience),

$\alpha_n$ and $\lambda_n$: are vectors of unknown parameters to be estimated and

$\eta_n$: normally distributed error term with mean 0.

From Figure 1, the structural model of the latent variable model can be written as:

$$X_n^* = KX_n + v_n\,, \quad v_n \sim N(0, \psi) \tag{2}$$

Where:

$X_n^*$: is a vector of the latent variable

$X_n$: is a vector of observed socio-demographic variables

K*: is a* vectors of unknown parameters to be estimated.

The structural model (equation 2), explains the latent variables in terms of the observed socio-demographic variables.

The latent attitude "PTLovers" as discussed in the previous section, was included in the integrated choice model. Equations (3) to (5) are the measurement equations for the latent attitude "PTLovers" according to equation (1). Equation (3) was normalised by setting the intercept to 0 and the coefficient of the latent attitude (PTLovers) to 1. (Ben-Akiva and Boccara, 1995)

$$\mathrm{Aff\_3} = \alpha_1 + \lambda_1 * PTLovers + \eta_1; \ \ \alpha_1 = 0, \qquad \lambda_1 = 1 \tag{3}$$
$$\mathrm{Aff\_4} = \alpha_2 + \lambda_2 * PTLovers + \eta_2 \tag{4}$$
$$\mathrm{Aff\_5} = \alpha_3 + \lambda_3 * PTLovers + \eta_3 \tag{5}$$

Similarly, as can be seen in Figure 1, five indicators were used to measure the latent attitude "Salience". Equations (6) to (10) are the measurement equations for the latent attitude "Salience". Again, Equation (10) was normalised by setting the intercept to 0 and the coefficient of the latent attitude (Salience) to 1.

$$\mathrm{Sal\_1} = \alpha_4 + \lambda_4 * Salience + \eta_4 \tag{6}$$
$$\mathrm{Sal\_2} = \alpha_5 + \lambda_5 * Salience + \eta_5 \tag{7}$$
$$\mathrm{Sal\_3} = \alpha_6 + \lambda_6 * Salience + \eta_6 \tag{8}$$
$$\mathrm{Sal\_4} = \alpha_7 + \lambda_7 * Salience + \eta_7 \tag{9}$$
$$\mathrm{Sal\_5} = \alpha_8 + \lambda_8 * Salience + \eta_8 \ ; \ \ \alpha_8 = 0, \qquad \lambda_8 = 1 \tag{10}$$

**Discrete Choice Sub-model**

The discrete choice sub-model consist of the measurement and structural models. Equation (11) is the structural component (utility function) of the discrete choice sub-model, it comprises of the systematic component V(.) and the random error component $\varepsilon_n$. The measurement component (choice model) of the discrete choice sub-model is given by equation (12). The mode choice was assumed to be between the recoded modal share, as discussed under section 4.2. These are private motorised modes (Car) which consist of taxi, car as driver and car as a passenger, Public transport (PT) which includes bus, tram and train, and Active modes (NMT), which comprises of walking and cycling.

$$U_n = \alpha + \beta X_n + \Gamma X_n^* + \varepsilon_n, \qquad \varepsilon_n \sim N(0, \Sigma_{\varepsilon_n}) \tag{11}$$

Where:

$U_n$: is the random utility of alternative n, $X_n$ is a vector of observed variables, $X_n^*$ is a vector of latent variables, α is the intercept of alternative n, β and Γ are matrices of unknown parameters to be estimated. $\varepsilon_n$ is a vector of the random error term, and $\Sigma\varepsilon_n$ is the covariance of the random error terms.

$$y_i = \begin{cases} 1, & \text{if} \quad U_i \geq U_{j,} \ \ \forall j \neq i \\ 0, & \qquad \text{otherwise} \end{cases} \quad i = Car, PT, \ NMT \tag{12}$$

Where:

$y_i$ is the choice indicator; this is 1 if an alternative is chosen, 0 otherwise

The likelihood of a respondent selecting a given mode is given by the joint probability of observing the alternative and the indicators of the latent attitudes ('*Affect'* and 'Salience'). If we assume that the choice of respondents is independent of each other, then the error terms (η, v and ε) of equations (1), (2) and (11) are independent of each other

The utilities for the three alternatives (Car, PT and NMT) in Table 6. PT mode was used as the reference mode (the intercept term was normalised to 0) in both the base model and the ICLV model.

Table 6: Model specification Table

| Variables | Base model | | | ICLV Model | | |
|---|---|---|---|---|---|---|
| | $U_{Car}$ | $U_{PT}$ | $U_{NMT}$ | $U_{Car}$ | $U_{PT}$ | $U_{NMT}$ |
| $ASC_{Car}$ | 1 | - | - | 1 | - | - |
| $ASC_{NMT}$ | - | - | 1 | - | - | 1 |
| $\beta_{Age\_NMT}$ | - | - | Age | - | - | *Age* |
| $\beta_{Age\_PT}$ | - | Age | - | - | Age | - |
| $\beta_{Cost\_Car}$ | Cost | - | - | Cost | - | - |
| $\beta_{Cost\_PT}$ | - | Cost | - | - | Cost | - |
| $\beta_{Dist\_NMT}$ | - | - | Trip Length | - | - | Trip Length |
| $\beta_{Educ\_NMT}$ | - | - | Educ | - | - | Educ |
| $\beta_{Gneder\_Car}$ | Gender | - | - | Gender | - | - |
| $\beta_{Income\_PT}$ | - | Income | - | - | Income | - |
| $\beta_{NCar\_Car}$ | Car Avail | - | - | Car Avail | | |
| $\beta_{TT\_Car}$ | TT_Car | - | - | TT_Car | - | - |
| $\beta_{TT\_PT}$ | - | TT_PT | - | - | TT_PT | - |
| $\beta_{Tr\_Freq}$ | Trip_Freq | - | - | Trip_Freq | - | - |
| $\beta_{WTime\_To\_BS}$ | Time to BS | - | - | Time to BS | - | - |
| $\beta_{Work\_Trip}$ | Work _Trip | - | - | Work _Trip | - | - |
| | | | | | | |
| **Attitudes** | | | | | | |
| $\beta_{Affect\_Car}$ | | | | Affect | | |
| $\beta_{Affect\_PT}$ | | | | | Affect | |
| $\beta_{Salience\_PT}$ | | | | | Salience | |
| | | | | | | |

### 5.4 Model Estimation

The sample size of 500 cases was divided into two (80% and 20%), 400 cases constituting 80% of the sample data was randomly selected from the sample data and used for the estimation of the choice models. The estimated model is then applied to the remaing 20% of sample data was used as out of sample data to estimate the choice probabilities, market shares and elasticities to validate the estimated models. The sections below discuss the model estimation and the model results.

## 6.0 Results and Discussions

## 6.1 Results

Estimation results of the MNL (base model) and the integrated choice and latent variable (ICLV) models are displayed in Table 7. All but one variable used in the base and ICLV models are statistically significant at least at 90% level. The only exception is Cost for private motorised mode, which was not significant . Table 8 shows the log-likelihood values for the two models; the values indicate that the

ICLV model is statistically superior to the based model. However, the log-likelihood of the ICLV model was estimated from its choice probabilities to ensure it is comparable with that of the base model. Table 7 presents the results of the two models tested using the framework in Figure 1. The base model without the latent variables and the integrated latent choice model with the incorporation of the latent model “Affect” and “Salience”.

Table 7: Model estimation results

| | **Base Model** | | | | **ICLV Model** | | |
|---|---|---|---|---|---|---|---|
| **Variable** | **Estimate** | **t-test** | **p-value** | | **Estimate** | **t-test** | **p-value** |
| $ASC_{Car}$ | -2.72 | --2.71 | 0.007 | | -3.18 | -2.86 | 0.004 |
| $ASC_{NMT}$ | -3.90 | -4.69 | 0.000 | | -3.85 | -3.87 | 0.000 |
| $\beta_{Age\_NMT}$ | -0.17 | --1.81 | 0.060 | | -0.23 | -2.48 | 0.013 |
| $\beta_{Age\_PT}$ | -0.37 | -1.46 | 0.145 | | -0.74 | -2.41 | 0.016 |
| $\beta_{Cost\_Car}$ | -0.10 | -1.02 | 0.310 | | -0.21 | -1.21 | 0.225 |
| $\beta_{Cost\_PT}$ | -3.10 | -2.43 | 0.015 | | -0.24 | -1.74 | 0.008 |
| $\beta_{Dist\_NMT}$ | -0.16 | -3.84 | 0.000 | | -0.18 | -3.53 | 0.000 |
| $\beta_{Educ\_NMT}$ | 0.51 | 3.99 | 0.000 | | 0.48 | 3.71 | 0.000 |
| $\beta_{Gneder\_Car}$ | 0.50 | 1.83 | 0.060 | | 0.53 | 1.97 | 0.048 |
| $\beta_{Income\_PT}$ | -0.17 | -1.75 | 0.080 | | -0.18 | -1.74 | 0.080 |
| $\beta_{NCar\_Car}$ | 1.87 | 8.67 | 0.000 | | 1.82 | 8.43 | 0.000 |
| $\beta_{TT\_car}$ | -0.40 | -2.41 | 0.016 | | -0.49 | -2.75 | 0.005 |
| $\beta_{TT\_PT}$ | -0.20 | -2.06 | 0.039 | | -0.20 | -2.02 | 0.043 |
| $\beta_{Tr\_Freq}$ | -0.23 | -2.20 | 0.028 | | -0.20 | -1.80 | 0.071 |
| $\beta_{WTime\_To\_BS}$ | 0.22 | 3.08 | 0.002 | | 0.20 | 2.57 | 0.010 |
| $\beta_{Work\_Trip}$ | -0.86 | -2.67 | 0.007 | | -0.18 | -2.41 | 0.032 |
| $\beta_{Affect\_Car}$ | | | | | - | - | - |
| $\beta_{Affect\_PT}$ | | | | | 0.62 | 2.70 | 0.006 |
| $\beta_{Salience\_PT}$ | | | | | -0.29 | -2.75 | 0.005 |
| **Attitudes** | | | | | | | |
| $ASC_{Aff}$ | | | | | 0.34 | 2.65 | 0.007 |
| $\beta_{Age\_Aff}$ | | | | | 0.38 | 3.29 | 0.001 |
| $\beta_{Age\_sal}$ | | | | | 0.42 | 2.93 | 0.003 |
| $\beta_{NCars\_sal}$ | | | | | 0.15 | 1.68 | 0.094 |
| $\beta_{Ridacard\_Aff}$ | | | | | 0.42 | 3.99 | 0.000 |
| | | | | | | | |

Table8: Model fit

| Index | Base Model | Latent Choice Model |
|---|---|---|
| **Log-Likelihood** | -82.42 | - 78.10 |
| **Rho-squared $\rho^2$** | 0.285 | 0.362 |
| **Adjusted $\rho^2$** | 0.248 | 0.355 |

Table 9: Percentage of predicted corrected

| Model | PT | Car | NMT |
|---|---|---|---|
| **Base Model** | 52.6% | 74.3% | 55.6% |
| **Latent Choice Model** | 65.8% | 77.1% | 63.0% |

Table 10: Classification table

| Observed | Predicted | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Base Model | | | | ICLV Model | | | |
| | **PT** | **Car** | **NMT** | **% Correct** | **PT** | **Car** | **NMT** | **% Correct** |
| **PT** | 20 | 8 | 10 | 52.6% | 25 | 7 | 6 | 65.8% |
| **Car** | 6 | 26 | 3 | 74.3% | 4 | 27 | 4 | 77.1% |
| **NMT** | 7 | 5 | 15 | 55.6% | 5 | 5 | 17 | 63.0% |
| **Market shares** | 33% | 39% | 28% | 61.0% | 34% | 39% | 27% | 69.0% |

Table 21: Time and Cost Elasticities

| Model | | PT | | Car | | NMT |
|---|---|---|---|---|---|---|
| | | **Trip Cost** | **Travel Time** | **Trip Cost** | **Travel Time** | **Trip Length** |
| **Base Model** | Cross Elast | 0.293 | 0.282 | 0.374 | 0.227 | |
| | Direct Elast | -0.629 | -0.385 | -0.516 | -0.419 | -2.330 |
| | | | | | | |
| **ICLV Model** | Cross Elast | 0.281 | 0.215 | 0.337 | 0.332 | |
| | Direct Elast | -0.464 | -0.376 | -0.639 | -0.511 | -3.000 |

Comparatively, Table 9 indicates the ICLV model well predicts the choice probabilities. Tables 10 expand on the results in Table 9 and present the classification table and market shares, which compares the observed and predicted outcomes of the alternatives together with the percentage of correct prediction. The results show that the ICLV model produces the highest percentage prediction for all the alternatives.

## 6.2 Discussions

We observe from the estimates in Table 7 that all the utility parameters of the modal attributes, individual characteristics and the latent attitudes, i.e. travel time, cost, distance, age, education and income have plausible values and the expected signs for both models (Johansson and Heldt, 2006; Yáñez, Raveau and Ortúzar, 2010; Kamargianni *et al.*, 2015). The estimates for both models are almost similar. The exception is travel cost for private motorised mode which has the expected sign but insignificant. However, we suspect this could be due to the high proportion of older respondents in the sample data;

most older residents aged 60 and over (29.4% in the sample) are entitled to free or subsidised travel on most public transport services in Scotland (Audit Scotland, 2010). Most respondents in this category either reported zero or small amount as travel cost.

To make the estimated effects more understandable, we estimated both direct and cross elasticities of travel time, travel cost and distance. The elasticity estimates listed in Table 11, indicate the percent changes in the probability of choosing an alternative given a 1% increase in an attribute of that alternative. For example, a direct elasticity of -0.511 in the ICLV model for travel time of private motorised mode implies the market share of private motorised mode reduces by 0.511% for a 1% increase in travel time. Cross elasticities show the percent changes of choosing an alternative given a 1% change in the attributes of a competing alternative. For instance, a cross elasticity of 0.337 in the ICLV model for the travel cost of private motorised mode implies that the market shares of private motorised modes will increase by 0.337% for a 1% increase in PT travel fares.

The direct time elasticities for private motorized modes for both models are higher than the ones for public transport, meaning that private motorised mode users are more sensitive to changes in their travel time and cost than users of public transport.

The travel time for private motorised mode and PT are observed to reduce the likelihood of choosing either alternative, travel time minimises the effect on the probability of observing either mode. The cross and direct elasticities displayed in Table 11 support this assertion and indicates an increase in travel time of either alternative will result in the reduction of demand. The values of the cross elasticity of demand of the alternatives suggest that private motorised mode and PT mode are substitute alternatives. The increase in the travel time of either alternative will increase demand for the alternative mode.

The results also reveal that active travelling is negatively impacted by trip length. The average walking and cycling distance were observed to be 3.4km and 5.6km respectively, while that for Private motorised mode and PT were 12.6km and 10.7km respectively. The results indicate that respondents are likely to walk for shorter distances. However, as distance increases beyond the acceptable threshold, the respondents will either drive or go by PT.

Work-related trips are found to reduce the utility for private motorised modes. This is intuitive due to the frequent and routine nature of such trips. They are more repetitive and less likely to change from day-to-day. The unemployed and the retired who do not make such regular trips were found to behave differently, possibly because they are less professionally active. The estimate for the trip characteristics (trip frequency) sheds more light on the argument above; frequent trips reduces the utility of private motorised mode.

The age of an individual is observed to have a significant impact on the likelihood to use active modes. Older individuals are less likely to use active modes of transport compared to younger individuals, possibly due to age-related mobility difficulties.

The educational level of individuals was found to have a significant impact on the choice of mode. It is seen that highly educated individuals tend to use active travel modes more, this is consistent with the conclusion in Atasoy et al. (2013). The higher the educational qualification of an individual, the more likely they are to choose an active or environmentally friendly mode of transport. Individuals in this class tend to be more sensitive to the environmental footprints of their behaviour, which is believed to explain the reason behind this observation.

The link between household income and car availability is well established in the literature (Ben-Akiva et al., 1999; Ortuzar and Willumsen, 2011; Kamargianni et al., 2015). The results confirm this finding and indicate that the higher the income of an individual, the more likely they are to own a car and, consequently, less likely they are to travel by public transport mode. The estimate of car availability increases the utility for private motorised mode and the likelihood of driving.

The combined walking time/distance from the trip origin to the first bus stop and the walking distance from the destination bus stop to the final trip destination has been observed to have a significant effect on the utility of a car. Increase in the total walking time increases the utility of car and the likelihood of driving (Yáñez, Raveau and Ortúzar, 2010). This effect is significant at 95% level in the base model and the ICLV model.

The latent attitude, Affect/PTLovers is observed to increase the utility of public transport and decreases the utility of private motorised mode. Individuals with positive valence towards public transport (high level of satisfaction for public transport services) have high utility for public transport in-vehicle travel time (Resnick, 2012). Additionally, environmentally conscious individuals use public transport more. This effect correlates with socio-demographic variables such as age and educational level; highly educated individuals tend to be more mindful of their carbon footprint.

The results suggest that salient experience on public transport represented by salience is found to decrease the utility of public transport mode. Experiences like anti-social behaviour, passenger annoyance and overcrowding on a bus could induce negative valence (such as the feeling of anger, embarrassment, frustration or fear). This could potentially hurt passenger loyalty. This observation is consistent with the findings in behavioural economics literature, which suggests that unusual and undesirable experience stays longer in human memory and looms more significant to the subject. Such experiences create intensely negative sentiments which could override otherwise rational course of action (Redelmeier, Rozin and Kahneman, 1993; Loewenstein et al., 2001; Kahneman, 2013). Ariely (2008) argued that salience is a form of anchoring and essential for consumer decision-making. Therefore, most prominent (pleasant or unpleasant) experience on PT such as any incidents of passenger annoyance or anti-social behaviour experienced by a passenger on a bus could have a far-reaching consequence on the future travel behaviour of users (Kahneman, 2013). Therefore, averting such experiences and addressing passenger complaints to their satisfaction could reverse the effects of such salient experiences, the associated negative valence (Resnick, 2012) and reduce the potential negative impact of the experience on future travel decisions (Dobbie, McConvile and Ormston, 2010; Metcalfe and Dolan, 2012a)

The study has defined key indicators (critical success factors CSF) for Affect and salience, using EFA and validated through CFA. The underlying indicators of Affect and Salience significantly influence decision-making and individual choice preference. The CSFs of Affect and Salience must be examined and accounted for through transport policy to increase the perceived utility of in-vehicle travel time for PT riders. Imposing sanctions on behaviours that are likely to induce intensely negative valence towards PT modes, and introducing high capacities buses during peak hours and increasing the frequency of vehicles could prevent overcrowding on carriages and improve user experience.

## 6.3 Conclusion

We estimated and compared two transport mode choice models, MNL model and ICLV model with the inclusion of two latent attitudes. The discussions above highlights the variables used in the two models and explains the impact of each variable on the decision-making process. The results have shown that the observed modal attributes, trip characteristics and individual socio-demographic variables have a significant effect on travel behaviour. Similarly, the result also indicates that underlying attitudes and perceptions influence the choice of transport mode. This suggests that travel behaviour is equally influenced by subjective variables (Avineri, 2011). Incorporating Affect, Salience and other similar latent attitudes as psychic cost (Elster, 1998) in the utility function of transport modes provides an added explanatory power to the choice models. The results of the study could have implications for public transport services. Accounting for these and similar subjective factors through transport policies and services could improve PT ridership. Public transport travel time and waiting time may be unforgiving, especially during inclement weather. However, operators and planners can improve user experience by creating the enabling environment to make the in-vehicle travel time productive. Addressing overcrowding and discouraging or penalising anti-social behaviours on PT carriages could mitigate the negative impact of user's sentiments associated with such experiences.

The results presented in this paper are limited to urban trips in one city in the United Kingdom. Additionally, the sample overrepresented older people in the population and those with high educational qualification.

Similarly, the study has shown that positive user experience and service satisfaction can create positive valence and sentiments in users towards the target object; this is revealed to increase the utility of PT modes.

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