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Designing Better Public Transport: Understanding Mode Choice Preferences Following the COVID-19 Pandemic

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Abstract: Transport behaviour has evidently changed following the COVID-19 pandemic, with lower usage across multiple modes of public transport and an increasing use of private vehicles. This is problematic as private vehicle use has been linked to an increase in traffic-related air pollutants, and consequently global warming and health-related issues. Hence, it is important to capture transport mode choice preferences following the pandemic, so that potential service changes can be made to address the lower usage. In total, 1138 respondents took part in an online discrete choice experiment methodology to quantify the utility of public transport service attributes in decision making around the choice of public transport. The data resulted in the development of three models using a multinomial logit model in R. For respondents on personal or commuting journeys, the mode of transport had no effect on utility. Results found that fare cost was the most important factor driving transport mode preference, when a range of choices were available. Following this, keeping fare cost consistent, faster journey times were preferred to stronger access to transport (i.e., through the provision of more bus stops/stations). The provision of operational relevant information to the journey was only significantly valued by commuters and travellers who could claim their journey as a business expense. Finally, when cost became less relevant (i.e., for travellers on expensed journeys), there was a significantly strong preference for taxi and road vehicle transport over all other transport modes. The results from this empirical research are discussed and the implications of recent transport policy are discussed, and recommendations of public transport service design are made.

Keywords: public transport; discrete choice; preferences; policy; service design; survey

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1. Introduction—The Importance of Public Transport Usage

Following the COVID-19 pandemic, there have been significant changes in public perceptions. In response to the virus, countries around the world introduced lockdowns and social distancing guidance in a bid to contain its transmission [1,2]. As a result, public transport usage fell by as much as 80–90% worldwide [3,4]. Despite the regulations around social distancing and lockdowns being relaxed, public perceptions have changed with a greater focus on transport hygiene [5], particularly given the fact that public transport had been identified as a potential vector for viral transmission [6]. As society begins to adjust to the new normal redefined by the pandemic, it is evident that transport patterns have changed. As many as 52% of transport users say they will use public transport less in the future and considering access to a private vehicle more important than before the pandemic [7]. This is illustrated by data from London, which found the rate of private vehicle use recovered faster than public transport modes; consequently, NO_x levels have returned to their pre-pandemic levels. This is problematic for a number of reasons.

The combustion of petrol and diesel fuels in vehicles generates pollutant exhaust emissions, such as carbon dioxide, nitrogen oxides and particulate matter—known collectively as traffic-related air pollutants (TRAPs)—all of which have been attributed to the acute rise in cardiovascular and respiratory diseases [8]. Furthermore, the burning of fossil fuels has long been established as one of the primary contributions towards global warming, amid increasing global energy demands [9]. In order to address these challenges, numerous countries have agreed to the Paris Climate Agreement target, in the UK this means achieving net zero emissions [10].

The transport sector is one of the more influential sectors for emissions [11]. Two key areas have been identified to meet net zero targets—reducing the use of fossil-fuel-based transport and reducing the use of private vehicle transport [10]. In the UK, a target has been set to ban the sale of all new petrol and diesel vehicles by 2025 [12]. This is alongside increasing areas of city environments being established as low-emission zones across Europe [13]. The move towards lower emission vehicles is underpinned by the fact that petrol and road diesel account for 58% of the fuel demand in the UK [14]. It is accepted that areas that feature a higher use of private motor vehicles, typically have more problems around greenhouse gas emissions, congestion and air quality [15]. Therefore, by reducing the number of private vehicles on the road, there can be better control over the emissions produced.

Public transport is largely accepted as a more energy efficient form of transportation. In comparison to a private motor vehicle (168 g/km), busses (103 g/km), rail (36 g/km) and tram/light rail (29 g/km) all emit lower carbon dioxide emissions per passenger kilometre travelled [16]. This is true for energy use. Private vehicles consume around 2–3 MJ/km, in comparison, busses consume 1 MJ/km and trams consume 0.3 MJ/km [17]. This would suggest that there are good justifications to encourage less use of privately owned vehicles and more usage of public transportation options.

However, despite trends such as the rising cost of private vehicle ownership, largely instigated by numerous governmental policies (such as higher vehicle tax), the evidence would suggest this does little to discourage private vehicle ownership [17]. For example, new vehicle registrations have increased year-on-year since 2009 [18]. There is a need to understand how public transport can be made a more attractive alternative option to private motor vehicles.

An array of factors can play a role in a person's decision to use public transport, such as the travel time, price and reliability [19], which affect the quality of the service provided. Together, these factors can influence a decision to use public transport over a private motor vehicle. For example, papers have looked into the effects of fares, quality of service, income and car ownership [20,21]. However, in the time since these papers have been published, there have been notable changes in attitudes towards private vehicles.

Given the need to shift to more sustainable forms of transport and the risk of a trends towards greater private vehicle usage (particularly in light of the COVID-19 pandemic), it is important to understand what drives decision making around the use of public transport. Specifically, by identifying service characteristics, these can be analysed for their influence on transport choice, hence allowing more targeted improvements and influences on policy.

1.1. COVID-19 in the UK Context

This study was conducted in October 2020. At the time, the first initial lockdown had come to an end approximately 5 months prior. The second national lockdown only occurred a month later in November 2020 [22]. Hence, the data captured in this study represent a population that was attempting to return to pre-pandemic travel patterns, making the timing of the questionnaire opportune to investigate the effects on public transport mode choice.

1.2. Aim and Objectives

This study aimed to quantify the usage of public transport following the lifting of the initial COVID-19 pandemic restrictions in the UK, with respect to key transport service characteristics.

In order to investigate this gap in knowledge, four objectives were established:

- Identifying, through literature searching and a focus group, the five most important factors that drive the choice of public transport;
- Designing and running an online discrete choice decision-making experiment;
- Conducting analyses of the data using a multinomial logit model;
- Deriving the relative importance of the different factors as well as a marginal willingness to pay estimate for each.

2. Literature Review

This literature review was conducted to recognise the validity of the use of discrete choice methodology in understanding the usage of public transport.

2.1. Discrete Choice Methodology

Human behaviour can ultimately be linked to decisions made regarding different choices of alternatives [23]. This could apply in many different contexts—for example, which healthcare provider a person chooses, their choice of consumer products and also the modes of transport they choose to use. The fundamental assumption is that this choice is rational, hence, we can then attribute a value given by the person to the outcome—this is known as utility [24]. This leads to the Random Utility Theory (RUT) which assumes that an individual makes their decisions to maximise utility and that a consumer behaves rationally, by making their choice based on their preferences, which is represented as a utility function. We can take advantage of this fact to experimentally ascertain preferences towards various features and attributes of a particular product or service. This method is called a Discrete Choice Experiment (DCE) [25,26]. By understanding the priorities towards service/product attributes, this plays an important role in developing and setting priorities in policy creation and design [27].

The key advantage of using DCEs is the evident congruence with consumer theory, allowing the calculation of willingness to pay (WTP), which is a key output from the method [28]. WTP is a measure of how willing to pay a person is for a single unit change of a particular attribute of the product or service [29]. However, DCEs are not without their drawbacks, namely, the combinations of attributes and levels can increase the response complexity for participants [30]. Hence, there are guidelines around the number of attributes and total number of choice sets participants are required to answer. Seventeen choice sets have been found to be the maximum number, above which the cognitive burden becomes too much [31]. Secondly, DCEs are based on hypothetical scenarios as opposed to real-world, observation-based data collection [32]. However, this is also an inherent strength in the methodology, allowing for the testing of a range of scenarios which would otherwise be practically difficult to achieve with a real-world trial. Finally, given that DCEs are primarily used in contexts of understanding behaviour to implement policy or service changes, there is a risk of strategic response behaviour, leading to over- or under-estimation of the resulting estimates [23]. Largely, the limitations of a DCE can be mitigated through good survey design and construction. As will be demonstrated later, the DCE developed for this paper used careful construction of the attributes and levels to reduce the cognitive burden on participants, as well as pivot the questionnaire scenario around one that the respondents will be familiar with.

DCEs have been used in many different contexts. For example, the method has been used in the development of health policy [33], employment decisions [26] and particularly in the transport research domain [23,34].

2.2. DCEs in the Transport Context

Primarily, the DCE allows for a better understanding of user needs in order to drive decision making around service design in situations where there are limited resources [35]. There have also been several studies that have addressed the UK in particular. For example, fare cost was found to have a negative impact on public transport utility, though this was dependant on factors such as the journey distance, type of traveller and income [20].

The results from this DCE would suggest that fare cost reductions should take priority over other service improvements with regard to user preferences. In a wider meta-analysis of literature, a significant, highly elastic relationship between income and value of travel time was established [36]. In the wider transport context, DCEs have been used to investigate a variety of aspects. For example, preferences towards car-free city centres [23], understanding the benefits and preferences towards ride-pooling services [37], understanding preferences for clean-fuel vehicles [34] and in assessing future automated vehicle preferences [38]. In all these papers, the recurring theme is around making policy or service changes based on user preferences. For instance, in their paper, around the appraisal of ride-pooling services, [37] was able to develop a set of requirements for future services, making DCEs a strong choice for user-centred design.

For this reason, DCEs are an ideal choice to explore the public transport preferences in the UK following the COVID-19 pandemic. In this case, the study was interested in evaluating a complex service and the subsequent policies required to support it, for which there is a consensus in the literature that DCEs are an ideal methodological choice for this aim [23].

To date, no other paper has explicitly used the DCE methodology to understand public transport preferences during this period of moving out of the pandemic, with all of the papers reviewed only considering transport in a pre-pandemic context. Hence, given the need to address the negative impact of the pandemic on the use of public transport, there needs to be an investigation as to how preferences have changed since the pandemic. There can then be a greater understanding as to whether current transport literature can still be relied upon given this new post-pandemic world.

3. Method

DCEs are a reliable method for engaging with a large population around their preferences regarding a complex service, such as public transport. In particular, it allows the attachment of a monetary value to attributes such as information provision and journey times. Unique to this study, is the context of the COVID-19 pandemic and the DCE lends itself well to an online questionnaire, which enabled participants to safely engage with the study from their own home. However, crucial to the validity and success of a DCE is the selection of the attributes and the presentation of a scenario that is relevant to the participant's travel experience [39]. The following sections will go into detail concerning the design and development of the DCE.

3.1. DCE Scenario

It is important that participants are presented with choices that can be real alternatives to each other. Hence, it was decided that journey distance would be consistent for all transport modes, based on the average commuting distance in 2015 of 8.8 miles [40]. We rounded this to 10 miles for simplicity, meaning the journey distance was kept consistent for all scenarios presented. Furthermore, three scenarios of: personal travel, commuting and expensed travel were considered. These were based on the analysis of most popular reasons for travel according to the UK Government's national travel survey [41].

- Personal journeys—journeys for personal reasons, such as shopping, holidays, family visits, healthcare, etc.
- Commuting journeys—journeys taken to travel to either work or education, typically taken on a regular basis.
- Expensed journeys—journeys where the traveller would not indirectly pay for their travel option. For example, business journeys where travel expenses could be claimed back, or a situation where a parent/guardian has paid for their child's ticket.

Participants were given a scenario that most likely matched their own personal travel experiences and were asked to consider the presented scenario.

3.2. Selection of Attributes and Levels

The selection of attributes is critical to the validity and strength of the DCE [39]. Using existing literature, the factors most important to users when using public transport were reviewed. Workshops were run with experts from Cenex and Nottingham City Council to determine the most appropriate and relevant list of attributes. Given the need to understand transport usage, these attributes were focussed on service-related attributes only. These attributes were collaboratively discussed, resulting in a shortlist of five, as is the standard procedure in many studies that have implemented DCEs [37,42]. For each attribute, three levels were chosen (except for transport type which had four levels). These levels were also the result of a detailed review of literature and UK governmental data from the Department for Transport (DfT) (and other sources) to gain extant market values as well as collaborations with transport research experts.

The five attributes chosen and corresponding levels are now described in detail below.

3.2.1. Transport Type

To address the aim of this study, it was important for the type of transport to be included in the list of public transport attributes. These were:

- Bus;
- Taxi;
- Tram/Underground;
- Train.

Trams and the underground were grouped together as in the UK, no city has both systems, but by describing both, this would be more inclusive. Air travel was not included as this was considered a different form of public transport, with fewer route choices where it would have been considered a realistic alternative transport mode. Secondly, air travel performs significantly worse in environmental emissions than all other transport options (244 g/km for domestic air travel) [16].

The taxi was added as while it is not considered a 'mass' public transport option, it is still viable alternative in almost all journeys where a bus, tram or train could be taken.

3.2.2. Fare Cost

The monetary expenditure required to use a transport mode has been identified as a key attribute [37,43]. Including this attribute in the DCE enabled the calculation of the marginal willingness to pay, which has been shown to be an influential factor in transportation research [38]. The levels of fare cost were based on extant market values, as well as data from governmental transport reports. Each transport type received their own three levels of appropriately set fare cost values, shown below in Table 1.

Table 1. Fare cost levels and justification.

Type	Fare Cost Levels (GBP/£)	Data Source
Bus	1.2/2.7/4.2	National Bus Fares Survey (TAS, 2018) and market data from transit services
Taxi	13/19/25	National Taxi Price Index (Reg Transfers, 2019)
Tram/ Underground	1.5/3.75/6	DfT data (Department for Transport, 2018) and market values from transit services
Train	5/9/13	Market values from train search engines (National Rail, 2021)

3.2.3. Travel Time (on Journey)

Travel time described the length of time the journey would take on the specific travel mode. This was important to calculate the willingness to pay (WTP). Furthermore, there is consensus across the literature that journey time is an important factor in the appraisal of public transport services [44,45].

Travel times that were appropriate to each travel mode were calculated, based on extant market values. This results in travel times that are different for each mode of transport; however, this is important for the creation of choice sets that are congruent to real-world scenarios. As also illustrated in [43], there are differences in how people perceive a 'fast' train compared to a 'fast' bus. Hence, it was important that for a consistent travel distance, the times were appropriately adjusted for each mode to ensure that the choice sets reviewed could be considered representative of a potential real-world journey, shown below in Table 2.

Table 2. Travel time levels and justification.

Type	Travel Time (Minutes)	Data Source
Bus	50/60/70	DfT average journey time data [46] along with values from mapping services
Taxi	25/30/35	
Tram/Underground	35/45/55	
Train	10/15/20	

3.2.4. Additional Travel Time

Additional travel time was found to be a key aspect of public transport use [47,48], describing the time required to, for example, travel to the train or bus station. It also accounted for average delays, based on data from UK government data [46,49,50]. Values were adapted appropriately to their corresponding transport type, to create realistic times and comparisons for the DCE. This was an important consideration as while trains are relatively fast in terms of travel time, the fact that there are fewer train stations than bus stops means there is, on average, a greater journey time to reach the mode of transport. Hence, it was important that this was reflected, so that a representative illustration of the total journey time could be considered by participants in the DCE, shown below in Table 3.

Table 3. Additional travel time levels and justification.

Type	Additional Travel Time (Minutes)	Justification
Bus	10/20/30	Transport for London data (Transport for London, 2019) and data from mapping services
Taxi	0/5/10	DfT data (Department for Transport, 2019) and mapping services
Tram/Underground	10/20/30	DfT data (Department for Transport, 2018) and mapping services
Train	20/30/40	DfT data (Department for Transport, 2019) and mapping services

3.2.5. Information Provision

Information provision provided information about the next stop, journey time remaining and current location. This was identified as a key aspect of the experience of public transport [51,52]. Three levels were denoted to this attribute, described as:

- None—no information provided on the journey;
- Some—some information, such as time of arrival;
- Much—much information is provided, such as real-time location information and the next upcoming station/stop.

3.3. Experimental Design

A D-Optimal design of 36 choice sets was generated using the R package "Support.CEs" [53]. For comparison, a full factorial experimental design would have yielded 324 choice sets. This was divided into three blocks of 12 (using Support.CEs [53]), with each participant completing one of these sets of 12. In total, 17 choice sets or lower have been found to be the ideal number to reduce cognitive burden [31]. The experimental design generated in R was then converted into HTML script and imported into Qualtrics using a STATA script presented in [54]. The script allowed for the efficient and reliable translation of the DCE into Qualtrics.

The presented scenarios were pivoted around trips of most relevance to the respondent. Three models were generated for each of the scenarios: personal travel, commuter travel and expensed travel. Participants were provided with a detailed description of each and were assigned one of the three travel scenarios, based on the demographic information they provided. The questionnaire was piloted internally with 10 participants to validate the language used as well as test the logic reliable for ensuring participants were only presented with travel scenarios relevant to their travel experience.

3.4. Data Collection and Sample

Data collection was facilitated using the Qualtrics Panels service. Hence, the DCE was presented as an online questionnaire. Considering the context of the COVID-19 pandemic, this online format allowed participants to complete the questionnaire in their own environment and device. The questionnaire was designed to be accessible and legible on both desktop and mobile devices. All respondents were checked for validity against their complete time. The sample size after validation was N = 1136. Below in Figure 1 is an example of the choice scenario that participants were given. As mentioned above, this was repeated 12 times to minimise the cognitive burden on participants.

	Option 1	**Option 2**
Transport Type	Tram	Bus
Fare Cost	£1.50	£1.20
Transit Time	35 minutes	50 minutes
Additional Transport Time	+20 minutes	+20 minutes
Route Information Provided	Some	Some

Your choice: Option 1 Option 2

Figure 1. Example of the choice scenario participants were presented with.

The sample is detailed below in Table 4. Across almost all measures, the sample collected in this study was comparable to the demographic proportional groups of the UK. This research was approved by the Institutional Review Board at Coventry University. Informed consent was obtained from each participant.

Table 4. Sociodemographic breakdown for complete dataset and travel scenarios (N = 1138).

Sociodemographic Variable	Total Sample Breakdown	Total (n = 1138)	Personal (n = 382)	Commute (n = 364)	Expensed (n = 392)
Gender	Female	593	205	170	218
	Male	544	177	193	174
	Other	1	0	1	0
Age	18–24	125	14	97	14
	25–34	217	56	100	61
	35–44	212	74	70	68
	45–54	244	93	51	100
	55–64	182	70	30	82
	65+	158	75	16	67
Ethnicity	Asian/Asian British	67	18	35	14
	Black/African/Caribbean Black British	37	7	14	16
	Mixed/Multiple ethnic groups	26	6	14	6
	White/White British	1004	349	301	354
	Other ethnic group	4	2	0	2
Region	Northern England	270	91	78	101
	Mid England	272	98	79	95
	Southern England	263	94	84	85
	Greater London	142	35	69	38
	Wales	54	15	20	19
	Scotland	104	37	28	39

3.5. Data Analysis

Data were analysed using the Multinomial Logit Model (MNL), increasingly used for the analysis of discrete choice experiments [55]. This was made possible using the mlogit package in R [56]. Data were initially reorganised using STATA scripts provided by [54] to reliably convert the raw data into a format readable by R.

4. Results

A total of 27,312 observations (1138 respondents × 2 alternatives × 12 choice sets) were recorded to feed into the estimation of the three models shown in Table 5. Assumptions were verified. The attributes of transport type (TYPE:XX) and information provision (SINFO and MINFO) were treated as categorical variables and consequently dummy-coded.

The personal, commuter and expensed travel models indicated McFadden's R^2 values of 0.202, 0.171 and 0.119, respectively. McFadden's R^2 values between 0.2 and 0.4 are considered to have 'excellent' model fit [57]. Log-likelihood was reported to be −988.35, −1632 and −1998 for the personal, commuter and expensed models, respectively. The Akaike Information Criterion was 2101, 3344 and 4085 for the personal, commuter and expensed models, respectively.

Table 5. Estimation results for personal, commuter and expensed travel (* $p < 0.05$, ** $p < 0.01$).

	Personal Travel (PERSONAL) (n = 382)			Commuter Travel (COMMUTE) (n = 364)			Expensed Travel (EXPENSED) (n = 392)		
	Coefficient	SE	z-Value	Coefficient	SE	z-Value	Coefficient	SE	z-Value
Intercept	0.245	0.569	0.572	0.214	0.270	0.791	0.465	0.308	1.508
Type:Taxi (TAXI)	−0.0399	0.306	−0.130	0.143	0.240	0.595	0.682 *	0.212	3.202
Type:Tram (TRAM)	−0.00351	0.144	−0.0243	0.0320	0.112	0.285	0.100	0.106	0.942
Type:Train (TRAIN)	−0.405	0.277	−1.458	−0.351	0.215	−1.627	0.0342	0.201	0.170
Fare Cost (FARE)	−0.144 **	0.0137	−11.909	−0.161 **	0.0106	−15.120	−0.119 **	0.00874	−13.708

Table 5. *Cont.*

	Personal Travel (PERSONAL) (n = 382)			Commuter Travel (COMMUTE) (n = 364)			Expensed Travel (EXPENSED) (n = 392)		
	Coefficient	**SE**	**z-Value**	**Coefficient**	**SE**	**z-Value**	**Coefficient**	**SE**	**z-Value**
Travel Time (TIME)	−0.0331 **	0.00556	−6.851	−0.0359 **	0.00427	−8.416	−0.0399 **	0.00398	−10.026
Ad. Travel Time (ATIME)	−0.0304 **	0.00649	−3.663	−0.0138 **	0.00513	−2.699	−0.0247 **	0.00431	−5.741
Some Information Provision (SINFO)	0.0413	0.121	0.339	0.246 *	0.0972	2.537	0.158 *	0.0797	1.991
Much Information Provision (MINFO)	−0.145	0.105	−1.372	−0.155	0.0819	−1.892	0.126	0.0741	1.705
Log-likelihood		−988.35			−1632.1			−1998.9	
McFadden's R^2		0.202			0.171			0.119	
AIC		2101.55			3344.121			4085.779	

Bus was set as the reference level for the model (Table 5). Similarly, for information provision, no information was set as the reference level. FARE, TIME and ATIME were all modelled as continuous variables.

4.1. Estimated Parameters

The calculated coefficients indicate the effect of each attribute on the overall utility. Across all models, FARE, TIME and ATIME had significant negative effects on overall utility ($p < 0.05$). This means that for every unit increase, this would correspond to a decrease in the likelihood of that transport option being chosen.

Looking more closely at FARE, this had the largest negative influence on utility for the commuter scenario ($ß_{COMMUTE:FARE} = -0.161$, $p < 0.001$ versus $ß_{PERSONAL:FARE} = -0.145$, $p < 0.001$ and $ß_{EXPENSED:FARE} = -0.120$, $p < 0.001$). Next, considering TIME, respondents were most sensitive to travel time for the expensed travel scenario ($ß_{EXPENSED:TIME} = -0.0399$, $p < 0.001$ versus, $ß_{PERSONAL:TIME} = -0.0331$, $p < 0.001$ and $ß_{COMMUTE:TIME} = -0.0359$, $p < 0.001$). ATIME had the largest negative influence on the personal travel scenario ($ß_{PERSONAL:ATIME} = -0.0304$, $p < 0.001$ versus, $ß_{COMMUTE:ATIME} = -0.0138$, $p < 0.001$ and $ß_{EXPENSED:ATIME} = -0.0247$, $p < 0.001$). These three attributes of FARE, TIME and ATIME were influential on the respondents' choice of public transport across all travel scenarios.

Unique only to the expensed travel scenario was the significance of the TYPE:TAXI attribute ($ß_{EXPENSED:TYPE:TAXI} = 0.682$, $p < 0.05$) in positively increasing the likelihood of that transport option being chosen. This was the only travel scenario where there was a significant influence of a specific transport option.

Similarly, unique only to the commuter and the expensed travel scenarios, the provision of 'some' travel information had a significant positive impact on the selection of a transport option ($ß_{COMMUTE:SINFO} = 0.246$, $p < 0.05$ and $ß_{EXPENSED:SINFO} = 0.158$, $p < 0.05$). For commuters, SINFO was the only significant positive impact on utility of all the attributes. While for the expensed scenario, SINFO had the second strongest influence on utility. This was not the case for personal travel, where information provision of any kind had no significant impact on choice.

4.2. Marginal Willingness to Pay

From the estimations calculated, WTP values for each of the attributes are reported. The marginal WTP is the marginal rate of substitution between an attribute and the price and is calculated as the ratio of the attribute estimation coefficient and the price estimated coefficient [23]. The value represents how much more or less a person is willing to pay for a unit increase or decrease in the attribute, whilst maintaining the utility constant. The results are shown below in Table 6.

Table 6. Marginal willingness to pay values (£/GBP) (* $p < 0.05$, ** $p < 0.01$).

	Personal	Commute	Expensed
TYPE:TAXI	n/a	n/a	5.73 *
TIME (£/min)	0.23 **	0.22 **	0.33 **
ATIME (£/min)	0.21 **	0.09 **	0.21 **
SINFO (£)	n/a	1.52 *	1.33 *

The marginal WTP values give an indication of which attributes are most valued by the respondents in their decision making for their choice of transport. The taxi was the only mode of transport that had a significant effect on choice. Participants who were given the expensed travel scenario were willing to spend GBP5.73 more on a taxi travel option. It was found that travel time valuation was highest for expensed travel, with respondents willing to pay GBP0.33 for each minute of travel time savings. In contrast, both the personal and commute models had similar willingness to pay values of GBP0.23 and GBP0.22, respectively. Considering the additional travel time (time spent journeying to the travel mode of choice), respondents valued both the personal and expensed travel scenarios the same at GBP0.21 per minute of additional travel time savings. In contrast, for respondents with the commute scenario, they valued travel time savings at GBP0.09 per minute, indicating that commuters were less willing to pay more for savings on the additional travel time. For the provision of some information on the mode of transport, commuters were willing to pay an extra GBP1.52, in contrast to respondents on the expensed scenario, who valued this less at GBP1.33. For respondents given the personal travel scenario, the effect of some information provision was not significant and hence had no impact on their willingness to pay.

5. Discussion

Public transport consumes less energy on average than private vehicles. However, vehicle usage data in the UK and worldwide would suggest that private vehicle usage remains high and the recent challenges around COVID-19 have compounded many of the trends away from public transport usage. This study aimed to quantify the influence of service characteristics that affect the selection of public transport. By gaining this information, a better and more robust understanding of what drives public transport acceptance and use can be gained, which can help focus the design of policies and schemes designed to increase the uptake of public transport.

5.1. Practical Implications for Public Transport Service Design

5.1.1. Fare Cost

The most influential negative factor in the perceived utility for personal and commuting journeys. This negative effect of fare cost was also observed in previous works [20,58]. Considering that most personal and commuting journeys in the UK are completed using private vehicles and that fare prices for public transport have increased at a rate greater than inflation, this will reduce the likelihood that private vehicle users will switch to using public transport more [59,60]. Service providers face a challenge of rising costs, meaning fare reductions are likely not possible without subsidies from government or industry sources.

5.1.2. Travel Time

Travel time was the second most negatively influencing factor on perceived utility. In-vehicle travel time is recognised as one of the most negatively influential factors on utility [61].

Respondents on both the personal and commuter scenarios valued travel time in a similar manner, GBP0.23/min and GBP0.22/min, respectively, suggesting congruence between the two sets of travellers. Hence, aiming to achieve faster travel but at a higher ticket fare, such as the High Speed 2 rail project in the UK [62], may have more limited utility. The increase in utility from travel time reductions, will be offset by a higher fare cost. While expensed journey travellers had a higher willingness to pay at GBP0.33/mile, fare cost still had a stronger negative effect on utility than travel time. However, there could be an effect of how expensed travel was defined. Expensed travel included both business travellers and passengers who may have had their ticket bought for them by a parent or guardian (and other scenarios where the ticket was not paid for by the traveller themselves), this may have reduced the clarity of the model. For example, as found in other discrete choice experiments, there is generally a higher influence of travel time savings than fare cost for business travellers [43]. In contrast, a situation where a traveller has had their ticket paid for them by family or friends, may still value the cost as an important factor. This may be an indication of this unexpected trend in the utility coefficients, as well as the McFadden's R^2 value of 0.119 for expensed travel.

5.1.3. Additional Travel Time

For both personal and expensed travel, respondents were willing to pay GBP0.21/min of additional travel time reduction; however, for commuters this was notably less at GBP0.09/min. This has been found in other research, highlighting the importance of service reliability in user satisfaction [63]. This suggests that policies aimed at improving public transport for commuters, should prioritise improvements to journey time and fare cost. The latest policies from the UK emphasise improving service reliability and journey times, by reducing the number of bus stops by up to 30% on some routes [64].

5.1.4. Information Provision

Some information provision had a positive effect on utility for both commuters and expensed travellers. For commuters, it was the single most positive influence on utility of all the attributes tested. This would suggest commuters and expensed travellers prefer to be informed of their trip status, for example, information around seat reservations and capacity has been shown to have a positive effect on train users' experiences [65]. This translates to a willingness to pay an extra GBP1.52 and GBP1.33, respectively, on their fare for the information, but anything beyond next stop/station or time to destination updates had no further positive effect on utility. We hypothesise that the information provided in the 'much' category can often be found in free, commonly available applications on smartphones, such as Moovit or City Mapper. In the UK, the smartphone penetration rate is around 78.9% of the population [66], hence it is likely respondents use these applications during their journeys, providing them access to detailed information. However, there is still a preference for some information to be presented on board; whether this is for convenience and ease of access is unknown and will require further research. Travellers on personal journeys were not willing to pay extra for this feature.

5.1.5. Taxi Travel

Taxi travel had the largest positive influence on utility for expensed travellers. It is indicative of the preference towards road vehicle type transport, when fare costs become less relevant (as it is an expensed journey). Therein lies a deeper problem around the perception of public transport and may explain the year-on-year increase in new vehicle registrations in the UK (though it should be noted that COVID-19 restrictions in 2020 on vehicle dealerships have resulted in the lowest number of vehicle registrations since 2009) [18]. While much remains to be proven, a requirement to achieve lower carbon emissions is to make public transport an attractive option, regardless of whether a taxi/single vehicle alternative is equally affordable.

5.2. Limitations

McFadden's R^2 values for the commuter and expensed scenarios fell below the 'excellent model fit' threshold; however, the models still succeeded in identifying the statistically significant relative differences between the attributes for public transport in the UK.

Discrete choice modelling can become infeasible and too cognitively demanding if the number of attributes grows too large [31,67]. For this reason, we focussed solely on service characteristics, but other factors such as transport design, weather and safety could also influence the perception of utility.

In support of the strength of this study, key demographic variables were comparable to the UK population. For example, this dataset consisted of 48% males, 52% females, in comparison to the UK's 49%/51% male/female split [68]. Across all other key variables, age, ethnicity and region, the sample achieved near identical proportional splits to the most recent UK data. The results should still only be interpreted within the context of this study. The variables that were not included in the scope of this study may influence the utility of the attributes assessed in this study and will need to be included in future research.

6. Conclusions

This research quantified the influence of several service characteristics on the choice of public transport. Five key attributes were shortlisted through detailed literature searching and focus groups with transport experts, with three types of journeys evaluated: personal travel, commuting to work or education and business or expensed travel. Using a discrete choice methodology, a total of 1138 participants took part using Qualtrics' panel service.

The discrete choice methodology uncovered several results, which were then used to derive recommendations for the design of public transport services and policy, which will be particularly relevant post COVID-19 pandemic as whilst trust in public transport may take time to recover, policy makers can focus on providing the utility that customer value most significantly.

- Journey time savings should not be implemented at the expense of higher fare costs. Fare cost had a stronger negative coefficient in all travel scenarios than journey time.
- If fare cost remains consistent, then providing faster travel times has a greater utility compared to decreasing the additional travel time (i.e., time travelling to stops or stations). This was most notable for commuters.
- Commuter and expensed traveller-focussed transport options should provide some level of information provision on board, such as next stop and delays. Some information provision was found to be the most significant positive factor for utility for commuters, but there was no further utility gained from providing a lot of detailed information.
- The strong preference towards taxis for those on expensed journeys suggest taxi drivers should focus their businesses on addressing the needs of these customers. On a wider level, this indicates a preference towards road vehicle travel when cost is not a concern.

These results, particularly those indicating a strong preference towards taxis when cost is not an issue, are indicative of the perceptions of mass public transport. It is important that mass public transport is seen as the default option, regardless of whether a private vehicle or taxi is affordable, to drive the kind of mobility change that can lower emissions. The results have shown that decisions on transport choice are complex and depend on the reason for travel, hence isolated policy changes to fare or journey times will not have a universal effect on increasing uptake in public transport. It will require a combination of improvements and this paper's results can be used to begin shaping the changes to the service characteristics required.

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