What are the values of a Green City? Estimating the willingness to pay (WTP) for attributes of a green city: An empirical study using Discrete Choice Experiment (DCE)

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Abstract

In recent decades, the Green City concept has received significant research attention, particularly in the areas of Urban Green Spaces (UGS) and transportation systems. However, little is known about changes in individuals' valuation of and preferences for green city concepts when a wide range of attributes are simultaneously considered. By implementing a discrete choice experiment (DCE) derived from Lancaster's characteristic model and random utility theory (RUT), this study attempts to measure individuals' preferences for Green Spaces in terms of their Willingness to Pay (WTP). Utilising the conditional logit model and mixed logit modelling technique as the main empirical strategy, results from the conducted online survey show that individuals tend to value urban green spaces the most, with a mean willingness to pay £117.61 on top of their current council tax amount per month for an improvement in this regard which coincides to correlations observed in similar research. This paper's findings can serve as a reference for city planners and researchers, informing them of which attributes of a green city should be prioritised.

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1. Introduction and Background

By the year 2050, it is estimated that more than half of the world's population will reside in cities, with projections indicating that 7 out of 10 people will primarily live in urban environments (FAO,2020). Changes in population density and demographic composition can present challenges in the supply chain and may raise further difficulties in managing the allocation of limited resources. Currently, urban environments account for over 70 per cent of the global food supply and 80 per cent of the global energy supply (FAO,2020). As the population migration from rural to urban increases, most developing countries have centred their infrastructure development towards urban areas. In the UK, 10% of the land is categorised as metropolitan areas, yet it counts for 40% of the total population. With a 6.9% growth rate in major conurbations between the year 2011-2019 (GOV.UK, 2021), these cities contributed to around 50-55% of the UK's total carbon emissions.

According to the UK government in 2021, Green spaces within urban areas fell from 63% in 2001 to 55% in 2018. Rapid urban expansions are often seen to be unregulated and poorly designed as demand for urban housing increases. This amalgamation of resources in prime city locations has also raised concerns over possible health problems and water-related environmental damage (UNITED NATIONS, 2022). For example, many of the newly constructed city buildings have not taken into consideration the necessary green architecture to minimise carbon emissions. As Wellbeing (2020) argues that green spaces can improve workers' productivity and increase well-being and that a well-balanced allocation of land usage between green spaces and industrial land can yield greater economic output while being sustainable, there is an urgent need for a stronger infrastructure to combat the lack of public amenities that could result in low labour productivity (Hossain & Huggins, 2021).

Over the last few decades, many countries have aligned their intention to tackle climate change issues, namely the inter-government agreements such as the COP23 and the Paris Agreement that, through land-use legislation, set out to raise public awareness of the urban environment. However, despite the effort, the percentage of UGS continues to see a decline in many cities' planning and designs.

The Green City concept was developed to resolve the ecological issues of conventional cities by implementing green infrastructures and related policies to improve the social well-being of urban residents while maintaining sustainable economic growth (Utami Azis, Eka Sari and Nirvana, 2019). This idea of accommodating geographical changes with an environmentally friendly approach has also been emphasised in one of the 17 Sustainable Development Goals[1] that focus on creating inclusive, safe, and sustainable human settlements (UNDESA, 2022). To propose suitable policy instruments that would help facilitate the effectiveness of relevant Environmental, Social and Governance (ESG) policies, it is important to identify and evaluate influencing attributes of Green Cities. Materialising such a concept calls for a collective effort from every impacted participant. The awareness of green city initiatives requires urgent attention from local administrations, particularly from residents that may be affected the most

[1] 11th Goal: Make cities and human settlements inclusive, safe, resilient and sustainable, See UNDESA (2022) P.48-P.49 for more details

by the changes in Green-Cities legalisations (FAO, 2020). By raising awareness of the benefits of living in an ecological city, active citizens can help speed up the transition process as they are better informed of the long-term value associated with cities' environmental, social, and institutional resilience (Buijs et al., 2016). According to Prasetiyo, Kamarudin, and Dewantara's (2019) study on environmental protection in relation to environmental awareness programs, civic engagement in environmental policies enhances residents' environmental awareness and inclination to endorse sustainable development (i.e., attach more value to sustainable development). Particularly, potential issues arising from rapid urbanisation could be resolved from a public perspective as part of green city initiatives. As mentioned by Hadjichambis et al. (2022), they find that the emergence of green cities may provide a platform to address city degradation and raise residents' awareness using Environmental Citizenship (EC) which focuses on using education as a policy instrument.

On the other hand, public perception of the concept of a greener city mainly surrounds the possible benefits of physical and mental well-being with increased access to urban green spaces, efficient and sustainable transportation, et cetera, with increased lobbying activities being seen in climate change that is pushing agenda for substantial renovation from scheduled urban city planning. For example, numerous city councils (local legislative bodies that manage urban areas in the UK) in 2021 reported to the cabinet office for their endorsement of a country-wide implementation of the 'Green City Plan', aiming to reduce carbon emissions through improving transportation, housing conditions and the number of green spaces to become net-zeros emissions by 2030 (Dawson, 2021) (Leggett, 2020).

While empirical evidence on the discovery and assessment of differentiated attributes of what constitutes a green city remains robust, scholars in economics have overlooked the usage of the discrete choice experiment for including the possibility of the existence of multiple-choice options. More specifically, many academics only consider the isolated effect of public transport networks, access to clean water and air, and other residents-related daily businesses on sustainable green city concepts. Given its research significance and the existing gap in economic literature, this dissertation investigates the aspects of transportation and how its consideration in the overall design of urban green spaces can provide indicative evidence to help improve and align current policies with targeted SDG development goals.

Given that the goal of the green city concept is to create a sustainable environment in the long run. This involves reducing the overall need for energy, decreasing negative environmental externalities caused by energy production, and promoting a liveable environment that enhances human welfare through increased access to green infrastructure and sustainable transportation which is the focus of this paper.

Focusing on integrating the aspect of transportation into future urban city planning, the paper also aims to determine the value of a green city with the use of the Willingness-To-Pay concept, henceforth WTP. This is a common approach amongst economists for finding individual preferences in choice models by measuring WTP, which can be elicited from a discrete choice experiment (DCE) constructed based on Lancaster's characteristic model and Random Utility Theory (RUT). The conditional logit model (CLM) and mixed logit model (XLM) will then be used to obtain the coefficient of an estimate for each attribute and thus identify which attribute of a city has the highest willingness-to-pay (WTP) ratio, estimated using preference space and WTP space specifications. This model is calibrated to reveal an individual's stated preference with data collected through a survey instrument 'Qualtrics' and analysis through 'Stata'.

2. Theoretical Framework

2.1 Discrete choice experiment

Environmental economists and city planners have been researching green cities and related studies on sustainable urban environments using discrete choice experiments (DCE) as a common approach, with publications and papers emphasising the significance of sustainable and Green City related policy. Thus, the use of DCE has become a standard method for revealing the stated preference. Researchers use it to uncover people's behavioural preferences and willingness to pay (WTP) for each specific attribute in each hypothetical setting (i.e., Alternative).

DCE is a type of choice modelling (Lancaster, 1966) developed in the 1970s to assess consumer behaviour and predict sales for new products effectively. Since then, economists have also adopted this approach in health and environmental economics, and it has proven to be effective. According to Kjaer's (2005) research, understanding the theoretical foundation of such a method is crucial, and choice analysis plays a significant role in this. By using the willingness to pay (WTP) estimation, it becomes possible to evaluate the degree of preference for each attribute, which provides valuable insights into an individual's willingness to forego the benefit or utility they desire. This approach is also backed by standard neoclassical consumer theory, which assumes consumers have rational preferences with individual aims to maximise the utility gained.

Unlike other choice techniques such as contingent ranking and contingent rating, DCE also has the advantage of less cognitively demanding surveys as it only requires participants to only provide information with regards to their preferred alternatives, which is less fatigue for them to make difficult decisions compared to other techniques.

It is important to acknowledge that while the simplistic approach to choice analysis in DCE can be beneficial, it also has some drawbacks. One potential issue is that it does not provide a strong preference order for all choices. In the context of this paper, participants were only given a dichotomous choice in each set of options due to the rarity of individuals residing in two settlements simultaneously in real life. Furthermore, the preferences observed in DCE may not necessarily reflect real market behaviour, as participants lack incentives to behave truthfully in hypothetical scenarios. As exemplified by Kjaer (2005), this hypothetical approach may lead to overestimation and hypothetical bias. Consequently, the lack of consequences in respondents' choices as they pretend to be in a real-life scenario may reveal their value for a particular attribute to be overstated.

As for the field of surveying, there are fewer potential obstacles, both theoretically and practically, as DCE is less cognitively complex than contingent ranking and rating. At the same time, this experiment provides preferences and information that is otherwise not achievable in the revealed preference method due to reality constraints in data analysis.

Therefore, DCE is a consistent approach to use for research on green cities and environmental policies, as it highlights attributes valued the most in any given hypothetical scenario and level settings. Since there is no market for these attributes, this is the most efficient approach aside from hedonic pricing.

2.1.1 Lancaster's characteristic model

Lancaster's characteristic model is an essential approach in evaluating the relationship of discrete choice experiments to the neo-classical economic theory that goods possess characteristics in a fixed proportion. The characteristic model lays the necessary theoretical framework for the DCE, and it is a theory that values the 'characteristic' of an attribute, where maximum utility is derived, rather than the traditional approach of valuing the direct utility gained straight from the attribute itself, according to Lancaster (1966).

This model emphasises the various distinctive outcomes that a single or a collection of attributes may provide, which become significant when analysing DCE results in the context of green city policy and can be achieved through DCE by putting attributes in various hypothetical combinations to value each attribute. Therefore, the WTP of each attribute can be assessed separately and as a whole using this characteristic model.

As an illustration, it is possible to measure the average addition to welfare gained (in the form of average marginal utility gained) from improved air quality due to additional urban green space (UGS) – which an individual attribute can provide. UGS offer a range of benefits (outcomes) for individuals to enjoy, assuming that the decision-makers are rational in their choices. These decision-makers seek to identify the optimal combination (choice) of attributes and levels that generate the highest possible utility while considering constraints such as the cost attribute (e.g. council tax). In addition, the implication of these attributes is fully known and objectively measured (Kjear, 2005). Thus, it enables the measurement for the Marginal Rate of Substitution (MRS) between two attributes. In the theme of Green City, this approach along with hedonic pricing are two methods that are the most suitable for assessing the value of its attributes, as mentioned before.

2.1.2 Random Utility Theory

Since the DCE sees an individual's behaviours as intrinsically probabilistic, of which external and internal factors can change their behaviour. Unlike probabilistic choice theory, Random utility theory (RUT) assumes people are deterministic and act rationally in their choices. Coinciding with Lancaster's Model and neo-classical theory, these assumptions imply an individual would always choose an alternative with the maximum utility gained as they are utility-maximiser. Which explains individuals' behaviour and provides a better prediction of which attribute an individual may pick.

$$U_{nj} = V_{nj} + \epsilon_{nj}$$

This equation of a utility function represents all the factors that might influence an individual's choice, with U_{nj} denoted as the total utility gained by an individual n from an alternative j. Though the total utility is not wholly observable, V_{nj} represents the observable utility gain and ϵ_{nj} represents the non-observable component (the error term) and is treated as a random component (Hanemann, 1984). This theory and equation implicate there is randomness in the reason why people deviate from their choices when the attributes and levels change, meaning there are random factors when individuals are not choosing an alternative that is most favourable to them. Hence the reason should not be known as these alternatives should remain mutually exclusive, denoted that two or more of the choices in DCE cannot happen simultaneously in each scenario. At the same time, maintain great consistency and a well-defined manner as an individual ranking these alternatives (Hoyos, 2010).

However, this theory might not capture the exact utility function of individuals due to asymmetrical preferences (Hess et al.,2008). Since each individual has different preferences with different values attached to each attribute which alters their respective utility function. Besides, the utility theory rationalises human behaviour as consumers might not be fully rational in their choices since they do not have the complete preference function (Kjear, 2005).

According to Manski (1973), they are four sources of randomness identified; they are a) Measurement errors and imperfect information b) Instrumental variables c) Unobserved attributes d) Unobserved taste variation. These factors may deter the appropriateness of the attribute chosen as a result.

This theory, together with Lancaster's demand theory, is used as an approach to DCE and forms the foundation for the technique employed to evaluate the value of Green City and its attributes. By estimating the observable component V_{nj}, the true utility can be determined, thereby enabling the determination of WTP.

2.2 Conditional Logit Model (CLM) and Mixed Logit Model (MLM)

The conditional logit model (CLM), also known as the multinomial logit model (MNL) in cases of multinomial choices, was developed by McFadden (1974) as an econometrical analysis tool for both revealed and stated preference data in DCE. It was intended to provide a theoretical framework for the empirical analysis of choice with finite sets of alternatives consisting of a bundle of attributes (Manski, 2001). CLM is also consistent with random utility theory and is computationally practical.

The independent variables in CLM come in two variations, alternative-specific and case-specific, respectively it refers to variables that describe the attributes and levels consisted in each alternative which varies across cases and within cases by alternative. In contrast, case-specific variables refer to variables that can be used to identify individuals which is constant within cases. The cases refer to all choice sets individuals faced in the survey, which consist of all the statistical observations (i.e., it also includes alternatives that respondents didn't choose in each choice set).

However, the assumption for the independence of irrelevant alternatives (IIA) in CLM lacks consideration for the heterogeneity amongst individual preferences, as IIA implies individual preferences are homogenous which drops consideration for external alternatives that is not shown in the choice set to the respondent. IIA assumes the relative likelihood of alternative $i \ and \ j$ do not depend upon or change regardless of the introduction of a third alternative in the choice set, which disregards external factors that are not considered in the survey's choice set. The relaxation of assumption for IIA in the mixed logit model (MLM) allows individuals to reconsider the relative likelihood of all alternatives offered in the choice set as the status quo is placed in the choice set. For example, if an individual is offered an alternative $i \ and \ j$ in the choice, CLM would assume the probability of $i \ and \ j$ to be chosen remains even when the status quo or other alternatives are included in the choice set. At the same time, MLM suggests that the inclusion of the status quo would change the overall probability of i , j and the status quo even if the third option is not chosen.

Therefore, MLM is more favourable in this research study. The drop in assumption of IIA enables MLM to gain better insights into each individual preference while considering the status quo. Besides, the consideration of the status quo in MLM means the individual's decision-making process is influenced by their current living condition, where these conditions might be shaped their perception of the status quo and they maybe attach more value and preferences towards features (attribute) that their settlement currently lack of. For example, suppose the individual's current settlement has limited UGS with poor public transportation systems. In that case, they are more likely to attach more value to more UGS access and public transportation options.

2.3 Willingness-to-pay (WTP)

As mentioned in section 2.1, willingness to pay is a monetary measurement of an individual's welfare change due to changes in the availability of public goods (Hanemann, 1991). The conventional welfare measures for price changes are compensating and equivalent variation (CV and EV, respectively). In the scope of this research study, the budget-constrained feature of the WTP approach to welfare measurement envisages researchers to evaluate the maximum amount of WTP an individual is willing to secure a gain in environmental improvement or the maximum amount of willingness-to-pay (WTA) if this change does not happen.

In addition, individuals might not be informed about Green City initiatives' use and non-use value. The use value refers to the attribute's value generated from direct or indirect consumption. In contrast, the non-use value refers to the attribute's value beyond current or future consumption, even if the individual never has and consumes it. For example, there might be a value in more green space now or later, even if individuals never use those spaces. This is also the value placed on an individual having the opportunity to use the green space in the future, known as the option value. In reality, individuals are likely only state their use value because use values are more visible and non-use value is less tangible, which is difficult to measure quantitively.

On the other hand, the inclusion of a cost attribute in the choice set enables participants to consider the cost of utility gained from the attribute, enabling researchers to elicit the WTP of each alternative while having the ability to enlist all attributes and levels into a single utility function for better comparison with other policies. In this paper, the cost attribute can be derived from an increase in the provision of the particular attribute (i.e., Council Tax). Hence, WTP can then be derived by comparing the marginal utility from the cost attribute against other non-cost attributes. Whilst by comparing the marginal utility of two non-cost attributes it would give the marginal rate of substitution with respect to one or the other attribute only.

Intuitively, the use of marginal willingness-to-pay (MWTP) in estimation can elicit the monetary amount of WTP in relation to the baseline of the cost attribute (council tax in this case). This indicative amount allows us to compare all attributes on the same scale, hence the word 'marginal' in this case refers to the size of change to a non-cost attribute as an additional unit of cost attribute is added to the baseline, where the individual's council tax payment amount is directly dominant to their respective baseline. In other words, MWTP can be interpreted as a marginal increase in utility gained given by the increase from the selected attribute.

3. Literature Review

Improving the greenness of a city has been at the centre of discussions in many economic, environmental, and social science literature papers. Focusing on the adoption of green cities, several research studies have been conducted using stated preferences to find the population's willingness-to-pay on urban green spaces (UGS) in relation to their resident distance (Del Saz Salazar, S., García Menéndez, L., 2007) as well as people's willingness to pay on improving public transport services in the city (Eboli, L., & Mazzulla, G.,2008). However, no academic study so far has investigated the combined effect of transportation and traditionally valued urban green spaces as a choice model. In the past, empirical studies paid careful attention to the overall effect of individual elements on green city performance. This approach to studying green spaces has, in fact, isolated the indirect effects of existing alternatives that consider a more active engagement from local urban residents (Hadjichambis et al., 2022). Conjunctively, the consideration of these two elements at once necessitates the use of a discrete choice experiment which will be explained in detail in this section.

Meginnis et al. (2021) stated that the CLM remained a standard estimation model in DCE studies and supported the importance of a carefully designed survey can facilitate the accuracy of the WTP outcome to respondents' true preferences. While in Bronnmann, J. et al. (2023) research on the naturalness of UGS, researchers used a discrete choice experiment for individuals' utility and a mixed logit model to derive an individual's willingness to pay for the naturalness of and walking distance to the closest UGS in 22 German cities. The author had emphasis that the CLM is not accurate enough to elicit the true WTP due to the lack of heterogeneous factors being considered. The WTP estimation, in this case uses two empirical specifications, namely, the WTP space and the preference space specification. In the WTP space model, naturalness is treated as a dummy variable and walking distances as distance quartiles. In the preference space model, walking distance is continuous.

Similar to Bronnmann, J. et al. (2023) research, this paper also utilises the discrete choice experiment to determine the utility provided by each attribute and derive the WTP using a mixed logit model in WTP space and preference space model. However, this paper also included a conditional logit model to account for the effect an individual's demographic may have on the WTP outcomes. This enables the showcasing of such effects in a mathematical manner by directly comparing the WTP values.

4. Methodology and Research Design

Recalling from the introduction, using DCE to estimate the WTP is a standard method and has been favoured by many published studies as it provides a monetary value of each individual's preferences and their value attachment for each attribute. The assumption that individuals would choose an alternative that yielded the maximum utility level under a budget constraint, and respondents observed choice in DCE could be elicited as an individual's preference (Hoyos, 2010).

While the theories presented in the theoretical framework serve as an important foundation for selecting the appropriate methodology, it is equally imperative to comprehend which attributes can be considered when evaluating a Green City. Two issues, namely, need to be resolved with the selection of attributes. Firstly, they need to be relevant to the requirements of the policymakers. Fundamentally, a relevant attribute would change the conclusions if ignoring its existence, and an irrelevant attribute would not change the consequence. Also, the researcher should be aware of mutually dependent and causally related attributes, as it is problematic that ignoring them can result in omitted variable bias (OVB) (Kjaer, T., 2005).

Secondly, selected attributes must be meaningful and important to the respondent. Predominantly, it is important to determine if an attribute is influential to the resulting outcome and can be accounted as a reason for their decision-making. Concerning Bennett and Blamey (2001), The demand-irrelevant attributes can become determinant and relevant if the level of consumer awareness and involvement is sufficient. Ignoring these attributes may result in biased estimates hence an inaccurate welfare measurement (Kjaer, T.,2005).

The conditional logit model (CLM) can then be utilised to interpret attribute importance. This model can analyse the probability of each alternative in a choice set. The assumption of independence of irrelevant alternatives (IIA) implies that the presence or absence of any additional alternatives in the choice set is not influential in the likelihood of a particular choice in this case. However, it has the disadvantage of causing biased utility estimation and OVB when the attributes in the model do not adhere to the assumption of IIA and the selection criteria above.

The violation of these requirements can be avoided to an extent by including interaction variables, in this case, these would be the respondent's sociodemographic information which acted as case-specific variables. With alternative-specific variables (I.e. attribute levels in each alternative), CLM can uncover the relationships between the individual's choice of alternative to certain attributes presented in the alternative. However, the IIA assumption in CLM is too simplistic as it assumes individuals' preferences are homogenous, whereby in practice, the preferences among individuals are heterogeneous.

As outlined in section 2.2, the mixed logit model (XLM) offers a more appealing approach due to its incorporation of interaction variables through considering interaction variables – referred to as case-specific variables in this choice model. It can be determined whether a distinctive subgroup with specific sociodemographic traits might affect the probability of a particular outcome (Choice) owing to heterogeneity in preferences.

To estimate the willingness-to-pay (WTP) for each characteristic of a Green City, this model can be fitted to determine the maximum likelihood of each alternative. This likelihood is conditional subject to the amount of respondent's information (McFadden,1974). Due to these complications associated with the model specification, the model is estimated by the ratio of the coefficients for all attributes of which this methodological approach is endorsed in the economic (Ebert, 2008) and health sectors (Liu et al.,2023) owing to its convenience and usefulness in interpreting research outcome.

4.1 Attribute selection

Like most empirical studies on Green Cities, attributes related to UGS (*Attribute: Availability of Urban Green Spaces (UGS)*) is taken into account. As evidenced by Anguluri and Narayanan (2017), Pukowiec-Kurda (2022) and Mortaheb and Jankowski (2023), UGS played a vital role in urban planning with many environmental benefits, suchlike its' contribution to minimising heat island effect and its' great effectiveness on improving resident's physical and mental wellbeing et cetera. It has traditionally been one of the main areas of study in green city topics. Thereby, it is included in the DCE due to its significance.

Unlike most empirical studies on Green Cities (particularly those around UGS), the DCE included transportation-related attributes (*Attribute: Availability of Non-Motorised Traffic Routes, Avg. Travel time change and Traffic priority)*. This is done as transportation takes a significant portion of air and noise pollution and an important role in the economic output of a city. Several studies on urban planning, including those by Lynch (1960), Romein and Trip (2009), and Dempsey, Brown, and Bramley (2012), have universally agreed on the crucial role of transportation systems in urban development strategy despite their differences in viewpoint. This study recognises the importance and emphasises that transportation systems should be considered as essential as green spaces.

Building a more inclusive environment for active transportation (I.e., cyclists and pedestrians), suchlike more bike lanes and giving priority to pedestrians and cyclists in the city design, can encourage people to use more of these methods of transport and reduce the use of motor vehicle—results in an improvement on human welfare through the reduction of carbon emission associated to motor transport.

4.1.1 Data collection

To identify the 'right' attributes for designing the survey, a 'pilot design' survey was laid out to 15 individuals at the University of Kent to give feedback based on a sample discrete choice set. Based on their responses, the attributes and levels are defined in Appendix 1. Specifically, through the results of the pilot design survey, council tax was selected as a cost attribute for DCE, this is a type of domestic property tax in the United Kingdom that is used for funding local municipal and emergency services as well as environmental infrastructures along with others. This payment vehicle allows us to determine individuals' willingness to pay for more environmental improvements in their city by assessing changes in council tax. Therefore, it is important to inquire about their current income since the payment method is funded from an individual's money income, and paying more would necessitate sacrificing other goods or services that require the respondent's money income to acquire.

In total, 107 respondents participated anonymously in an online survey, with 80 people responding and 63 people answering the survey completely (Around 59% of positive response rate). Amongst those remains, they are excluded from the data set due to inconceivable answers and incompleteness in answering the DCE section, as it is vital for data analysis. It is to be noted that 38 of those 63 people are full-time students, 63.64% of respondents are from the United Kingdom, and 36.36% are from elsewhere. The average time to complete the survey is 9 minutes and 5 seconds.

4.1.2 Experimental design

Throughout the design process, a modified Fedorov algorithm defined the hypothetical setting of the levels and attributes that form a choice set in the DCE (Carlsson, F., & Martinsson, P.,2003). This algorithm maximises the D-efficiency of the design by using the covariance matrix of the conditional logit model (CLM) as a basis for the choice set design, producing an efficient full factorial design for DCE (Arne Risa Hole, 2015). This efficient full factorial design was computed using "dcreate" module function on STATA software and aims to force respondents to consider all the attributes and levels shown in the choice set and not just those extremes, given that the hypothetical alternatives offered in the choice sets are comparable to avoid dominating choices.

Table 1: Sample of a discrete choice set

	City 1	City 2	Environment you currently live in
Availability of Non-motorised traffic routes	No segregated bike lane nor pedestrian zone	Limited segregated bike lane and pedestrian zone	
Average Travel Time (% change)	-20%	+20%	
Council Tax (% change)	-10%	+20%	
Distance to primary businesses	Same as your current distance	2 Miles further	
Availability of Urban Green Spaces (UGS)	Large parks with no other green spaces	Limited parks and on street green spaces	
Traffic Priority	Pedestrian	Motor	

The survey consisted of two sections. In the first section, participants of the survey are asked questions related to their sociodemographics and state their current living conditions, namely the availability of urban green spaces close to their home, the amount of council tax paid and their education status etc., all the attributes and levels used in the DCE are fully listed in Appendix 2.

In the second section, the survey is branched into 2 blocks of questions as it is ideal for the survey to be less fatiguing to answer while maintaining a sufficient number of choice sets in the survey design – 30 choice sets in this case. To determine which block of questions each individual belongs to, we use even or odd birthday as a grouping criterion because it needs to be an exogenous factor to the DCE to avoid bias between the two blocks. The result shows that 40.35% of respondents have a birthday on an odd day, and 59.65% have a birthday on an even day.

Each block comprises 15 questions (Choice sets) that contain the DCE, each question consists of two hypothetical choice sets (alternatives), and one status quo is offered to allow respondents to state their choices and stated preferences. Table 1 shows an example of a choice set used in the experiment, where the two alternatives are 'City1' and 'City 2', and the status quo is 'Environment you currently live in'. Specifically, the attributes in each respondent's status quo are characterised by the sociodemographic information they provided in the first section. They were instructed to use their responses from that section to indicate their status quo in the DCE. Consequently, the levels of the attribute "Average Travel Time," "Council Tax," and "Distance to Primary Businesses" were adjusted respectively in percentage and distance changes, based on the respondents' status quo levels. This decision was made based on high variances observed in these attributes during the pilot design survey. If fixed values were used, dominant choices might occur owing to significant differences between the presented levels and the respondents' status quo.

The objective of the first section is to reveal the respondent’s current socio-economical background and information related to their current living condition. Importantly, this information enables respondents to reflect their current living conditions to the corresponding levels for each attribute shown in the choice set as status quo later in the DCE. At the same time, this enables us to use it as case-specific variables in data analysis to identify each individual.

In the second section of DCE, the respondent was asked to choose which of the 2 cities with their status quo they would prefer to live in, excluding the consideration for cost and time in resettlement and taking consideration solely based on the attributes and levels shown in each question only, intending to limit external factors that may deter the outcome of their choice. Also, the respondent wasn’t given an option for ‘no choice’. This is done as the preference for not choosing can be incorporated with the status quo. It contains a more comprehensive inventory of preferences given that the specification of not choosing can be incorporated into a more general utility framework by treating no choice as just an option (Status quo). In Dhar's (1997) article, they found that the status quo has certain psychological advantages. In other words, it allows a person not to make a decision at all in order to avoid negative outcomes and maintain the flexibility to choose in the future (Dhar, 1997).

At the same time, preference from those individuals can still be obtained since the choice contains their sociodemographic and living conditions that can correspond directly to levels and attributes presented in the choice set in this study. In real life, opt-out is not an eligible alternative as you cannot ‘not’ living in anywhere. Instead, they have a choice to move somewhere else or stay where they are. Back to the hypothetical setting, this potentially may avoid an unrealistic and undermine the validity of DCE that not choosing an option may cause (Sever, Verbič and Sever 2019).

4.2 Data Analysis

Given the above assumptions in the theoretical framework, it suggests that individuals will only select the alternative that yields the highest level of utility (i.e., the most desirable option) for them. Therefore, it is ideal for maximising the proportion of observable components of the utility function to achieve a more precise estimation of the value of total utility gained. In this research study, we adapt the random utility model (RUM) to find the true utility function of an individual n from an alternative i which is given as:

$$U_{ni} = -\beta'_{1,n} CouncilTax_i + \beta'_{ni} x_i + \epsilon_{ni}$$

Where the observed component’s V_{ni} from 2.1.2 RUT is adapted as $V_{ni} = -\beta'_{1,n} + \beta'_{n}$. Besides, $-\beta_{1,n}$ is the cost coefficient of the cost attribute Council Tax and $\epsilon_{ni,t}$ is mutually independent and identically distributed random variable (i.i.d.). There is no n presence in the observed components in CLM; it assumes all respondents are represented with the same level meaning

a_n and β_n are identical for all individuals, assuming the respondent's preferences are homogeneous. To evaluate the importance of each attribute, the conditional logit model (CLM) can be used to find the probability of choice by an individual (Gonzalez 2019) given as:

$$P(C = j|i, j) = \frac{e^{V(\beta, X_j)}}{e^{V(\beta, X_j)} + e^{V(\beta, X_i)}} = \frac{1}{1 + e^{V(\beta, X_i) - V(\beta, X_j)}}$$

Where P represents the probability of choice for alternative j when alternative j and i are available. However, it is acknowledged there is heterogeneity among individual preferences hence the assumption for IIA is dropped, a mixed logit model (XLM) can be derived as:

$$U_{ni} = -\beta'_{1,n}CouncilTax_{ni} + \beta'_n x_{ni} + \epsilon_{ni}$$

Where n is included in all attributes, which assumes each individual n has a set of random coefficients representing an individual preference for each attribute. Consequentially, the utility function for the alternative i becomes:

$$\begin{aligned} U_i = \beta(&-\beta_1 CouncilTax_i + \beta_2 Avg.TravelTime_i + \beta_3 NonMotorisedTrafficRoutes_i \\ &+ \beta_4 DistanceToPrimaryBusinesses_i + \beta_5 UrbanGreenSpaces_i \\ &+ \beta_6 TrafficPriority_i) + \epsilon_i \end{aligned}$$

Where $\beta = -\beta_1 + \beta_2 + \beta_2$ ... is the weighting parameters of the attributes which can be used to derive for linear combinations. This approach allows every multi-attribute profile to be converted into a singular point on the continuous number line where council tax denotes the cost attribute of the alternative measured by the respondent's stated council tax level with the proposed percentage change in the alternative.

Also, $x_i = -CouncilTax_i + Avg.TravelTime_i + NonMotorisedTrafficRoutes_i$ ... is the vector of attributes with levels of qualitative attributes dummy-coded. This utility function can then derive WTP for changes in non-cost attributes by estimating marginal willingness-to-pay (MWTP), defined as the marginal rate of substitution (MRS):

$$MWTP_i = \frac{dx_i}{dU_{income}} = \frac{dx_i}{dp} = \frac{\beta_{x_i}}{-\beta_{CouncilTax}}$$

Where i in this equation represents the range of attributes of interest relative to the cost attribute, signifies that the attributes change respectively to changes in council tax and specified there is linearity amongst parameters and explanatory variables (Kjaer, T.,2005), this standard approach to DCE implies the relationships between them are linear (Lancsar, Fiebig and Hole 2017). Also, this estimation is preference space meaning β_{xi} and $-\beta_{CouncilTax}$ are respectively normal and log-normal distributed random coefficients implying the error surrounding MWTP follows a Cauchy distribution.

Subsequently, the same WTP estimate can be elicited from XLM using the WTP space model by redefining the utility function as follows:

$$U_{ni} = -\lambda(\varpi'_n x_{ni} + CouncilTax_n) + \epsilon_{ni}$$

Where $\lambda = \beta_{CouncilTax}$, $\varpi = \frac{\beta_i}{-\beta_{CouncilTax}}$ and $x_{ni} = Non\ cost\ attributes\ of\ interest.$ With this equation, the individual n WTP for attribute i can be measured directly in monetary value, assuming that heterogeneity in this specification is directly imposed on the WTP parameters (Bronnmann, J. et al., 2023). Despite these two specifications being equivalent to each other, WTP space has the comparative advantage of producing immediately interpretable results while keeping the variance relatively low. Unfortunately, this model is non-convex in its' log-likelihood estimate since the utility function is not linear in parameters anymore. Besides, it suffers from a lack of statistical resources that can be used in real life of which statistical software is currently mostly built on preference space models for MWTP.

Intuitively, the preference space model is generally a better fit for the dataset (Train and Weeks 2005) and offers better flexibility considering it gives the substitution relative to a change in the utility of the average individual current income, known as the WTP. This allows for more complexity between non-cost attributes and uncovers individual willingness to pay by these attributes. In addition, this model can account for the issue of incomplete information that people may have on their preferences, as well as consider factors that are unobserved but still have an impact on their preferences.

The survey responses were manipulated in such a way as to allow the statistical software 'STATA' to run choice modelling, this was done by dummy-coded all the non-cost qualitative attributes and listing all the levels of all attributes. In both estimation specifications, the variables $council\ tax, Average\ Travel\ Time\ and\ Distance\ to\ primary\ businesses$ were treated as continuous while the other non-cost variables as dummy variables. To be noted, the qualitative attributes with more than two levels are dummy coded into two levels only in the regression estimations. This is done to avoid dummy variable traps, which occur when the number of levels in an attribute equals the number of dummy variables—leading to multicollinearity as they become perfectly correlated, causing the estimate to be inaccurate.

Ultimately, both specifications aim to find the change in the council tax relative to changes in attribute i which can be represented as WTP (when the value is positive) or WTA (when the value is negative) that have real economic meaning.

5. Empirical Result

This section will present results on an individual's MWTP of all attributes in DCE with the heterogeneous effects of an individual's preferences. In all estimates, vectors of attributes and individual sociodemographics are included in MWTP and XLM. These empirical specifications can then be elicited for individual WTP hence uncovering their respective preferences on attributes by comparing WTP where higher WTP is assumed while deemed to be favourable by the individual in the DCE given RUT assumption of utility maximisers. Importantly, the coefficient from Tables 2 and 3 (reproduced in Appendix 1) represents the weighting parameters of each attribute therefore, these coefficients shall not be interpreted as MWTP directly. Besides, It is critical to interpret MWTP as an additional amount of council tax paid to increase a particular attribute level which is expressed in GBP per month. Unlike percentage change, which measures the proportional differences between two values relative to the variables' base value, MWTP describes WTP for a specific attribute level.

CLM was first used to present the average impact of the DCE to WTP as preferences heterogeneity is disregarded (assuming preferences are homogeneous) to value the attributes equally. Implicating that the preferences of each individual are ‘stable’ (Kjaer, T.,2005), offering more flexibility and computational simplicity than XLM because IIA assumption enables us to reduce the complexity that heterogeneity preferences may involve while making DCE simpler to predict preferences with a greater degree of robustness.

Table 4: Willingness to pay of Individuals on selected attributes by a conditional logit model

Attribute name	Attribute Level	S.E.	Marginal willingness to pay (MWTP)
Traffic priority	Priority for cyclist	0.17734	22.27
	Priority for pedestrian	0.23082	61.96
Bike Lane Segregation	Fully segregated bike lane	0.22146	34.22
	Limited segregated bike lane	0.18788	9.63
Urban Green Spaces coverage	Comprehensive Urban Green Spaces	0.22966	34.15
	Limited Urban Green Spaces	0.21455	96.82
Distance to Primary Businesses	(+2, 0, -2 miles change to respondent’s stated level)	0.04831	11.47
Average Travel Time to Work or School	(20%, 0%, -20% change to respondent’s stated level)	0.00720	(1.21)

However, given that the aim is to uncover the WTP of individuals with minimal difference between stated and real-world preferences. It becomes necessary to consider heterogeneity preferences, hence why we are using an XLM with the assumption for IIA dropped to find the results for this matter. In this model, the effect of an individual's sociodemographic on WTP is categorised into case-specific variables. As evidenced in section 3, these variables provide a subdivision of the existing dataset that can be used later to find individuals with certain sociodemographic traits that are influential to the research outcome.

Table 5: Willingness to pay of Individuals on selected attributes by a mixed logit model

Attribute name	**Attribute Level**	**S.E.**	**Marginal willingness to pay (MWTP)**
Traffic priority	Priority for cyclist	0.18073	6.26
	Priority for pedestrian	0.22022	29.36
Bike Lane Segregation	Fully segregated bike lane	0.19129	31
	Limited segregated bike lane	0.21274	13.76
Urban Green Spaces coverage	Comprehensive Urban Green Spaces	0.17814	18.74
	Limited Urban Green Spaces	0.23129	98.87
Distance to Primary Businesses	(+2, 0, -2 miles change to respondent's stated level)	0.04814	11.95
Average Travel Time to Work or School	(20%, 0%, -20% change to respondent's stated level)	0.04625	(3.26)

Although the result presented in CLM in Table 4 indicates an individual's average MWTP, the average MWTP is likely to vary across individuals based on their sociodemographics. Further investigation with the inclusion of heterogeneity would be required. Thus, it necessitates using XLM in Table 5 to assess whether the effect on MWTP remains under different sociodemographics of individuals.

According to Tables 2 and 3, the MWTP estimate of having comprehensive UGS in the city is given as follows:

$$mWTP_{FullUGS} = \frac{\beta_{FullUGS}}{-\beta_{CouncilTax}} = \frac{0.0885315}{-(-0.0047231)} = 18.74$$

This implies that individuals are willing to pay £18.74 more in council tax to have the best possible (comprehensive UGS) urban environment they live in or visit. Looking into the MWTP, the marginal change of this estimate has the comparative advantage of standardising results as the change in utility relative to one additional unit of environmental improvement.

Whereas the MWTP for average travel time to work or school is as follows:

$$mWTP_{AVGtravTime} = \frac{\beta_{AVGtravTime}}{-\beta_{CouncilTax}} = -3.26$$

According to the equation, for every extra 10 minutes of travel time, individuals are willing to pay £3.26 less in council tax. Conversely, they are willing to pay £3.26 more in council tax for every 10 minutes less of travel time to work or school. While if efforts to reduce travel time are not made, individuals are willing to accept an average of £3.26 reduction to council tax for every 10 extra minutes of travel time.

On the other hand, every two miles added to the distance to primary businesses leads to an £11.95 decrease in willingness from not paying for council tax which can also be converted to an £11.95 increase in willingness to pay for two miles less in the distance to primary businesses. Individuals are willing to pay an average £6.26 increase in council tax for cycling as a traffic priority in the city.

Among all attributes enlisted in Table 5, we identified that individuals have the highest willingness to pay for improving UGS with an average of £18.74 increase in council tax for a comprehensive UGS in their urban settlement. In contrast, individuals have the lowest willingness to pay for a reduction in average travel time, with a £3.26 increase for every 10 minutes reduction in travel time.

In general, the inclusion of interaction variables (Table 5) results has a positive difference compared to results that are without them (Table 4), besides the robustness of the results can be tested. The implication of these positive differences implies the average MWTP would increase with the inclusion of interaction variables. Moreover, the differences in MWTP are subtle with the exception of attribute $Priority\ for\ Pedestrain$ where the differences of MWTP without interaction variables is around 2.11 times more than with interaction variables while the one attributes with the lowest differences is $Distance\ to\ Primary\ Businesses$ with only a 4.18 per cent differences. Positively, the reason behind such observations may rely on the additional accuracy these variables provide to the logit model.

With reference to Appendix 2, the case-specific variables used in the conditional logit model and mixed logit model are basically the respondent's sociodemographic, it covers 1) the method of transportation used most, 2) Gender, 3) Age, 4) Employment status, 5) Education, 6) Current money income, 7) Living in an urban environment, 8) Is a homeowner and 9) Council tax level. Out of all the information enlisted above, the respondent's council tax level had a very preponderant role in serving as a baseline for the change in council tax to the subsequent change in utility gained from an increase of selection attribute thus for all estimations, which provides a meaningful economic measurement as WTP.

6. Limitations

Although the respondent's current living condition may fully reflect the status quo in XLM indicated in the survey's respondents' information, an individual's perception of their status quo might change due to external factors. For example, an individual may prefer to live in rural environments, and high living costs in the city may discourage them from living in urban environments, et cetera. The inclusion of questions related to certain external factors in the survey may not be feasible due to their added complexities. Additional questions on such factors may cause respondents to find it more cognitively demanding, which goes beyond this study's scope. Resultingly, the paper acknowledges this behavioural in the decision-making process: not everyone follows the utility maximiser principle as stated in RUM.

Further research would be beneficial if researchers increased the scope of the survey audience to balance the sample weighting for participants with different sociodemographics in the survey. Nonetheless, this estimation bias associated with external factors can be overcome thanks to the hypothetical nature of DCE, enabling us to manipulate the hypothetical in such a way as to avoid such influence on individuals' behaviour in the decision-making process, which enlarges the size of the observed component in the utility function along with limiting any estimation bias.

As mentioned in the Data Collection section, 38 out of 63 respondents are identified as a student in the survey, which accounts for 60.32% of the total sample size. It can be problematic as it can pose selection bias to the research outcome, and the data cannot be defined as representing the whole population. In particular, the number of survey respondents that completed the survey entirely ultimately decreased the number from 88 to 63 respondents, given that the test got to be robust and meaningful to interpret. These estimates (MWTP), along with heterogeneity based on a relatively small number of observations, may suffer from lower statistical power. However, the results and relationships presented should be like survey results conducted on larger and more diverse scales in UK and Europe. Furthermore, a significant portion of respondents is students, insinuating that the data is able to better uncover their decision-making behaviour via WTP.

The potential cause of selection bias may arise from the distribution channel, with 39.68% of the sampling population accessing this survey through social media platforms. Despite countermeasures being implemented, such as extensive designs for constructing ‘realistic’ hypothetical scenarios and distributing the survey through multiple channels, including social media platforms (Instagram, LinkedIn, Snap Chat), QR code and Email distribution. These weighting differences in the sample population may likely increase the likelihood of the estimate being skewed, thereby rendering biased research outcomes (Rebecca Anne Dobra *et al.* 2021). This potential hindrance may become more probable when the sample population is divided under different analytical specifications.

As noted in Table 2 and Table 3, the results show that the p-value of most variables from both CLM and XLM is higher than 0.05, suggesting that the results are largely statistically insignificant and that the data outcome cannot reject the null hypothesis or accept it. In case of green cities has largely differed in papers that also investigate this topic; possible causes of such statistically insignificant can be the differences in the specifications of transportation-related attributes and UGS-related attributes, where they can have many variables involved in each. Thus, the results can only be served for illustrative purposes.

This could be problematic as too many variables can lead to overfitting the model, losing the ability to generalisation. Whilst small population size and unobserved behaviour may also contribute to such effects, we believe the data can still be practically significant to the research outcome due to a similar pattern of results observed after comparing several empirical results, including Bronnmann, J. et al. (2023) study on naturalness in UGS. Conversely, being statistically insignificant does not directly imply the results are practically insignificant or not meaningful. Still, it should focus on the magnitude of the WTP and the confidence interval surrounding the estimate, particularly in the case of the WTP space model where non-convexity in likelihood can occur when the cost attribute is log-normally distributed and affects the model fitting where no convergence can be achieved.

Regarding section 2.1.2, the random utility theory (RUT) provides the assumption that individuals are rational and deterministic. Though in reality, the participant may have ‘drifted away’ from behaving rationally due to external factors and made decisions that are not in their best interest (i.e. acting as utility maximiser).

Recalling from section 4.1, it is noted that the preference space specifications suffer from high variance in WTP due to its’ normal or log-normal distribution nature. While being convenient to assume and usually specified beforehand (Train and Weeks 2005), these distributions come with different implications that provide less reasonable distributions of WTP. Therefore, we resolve these by using the WTP space model. However, this model suffers from low convexity in log-likelihood that poses a more significant problem than the preference space model; thus, it can be resolved by posing more reasonable distributions of WTP.

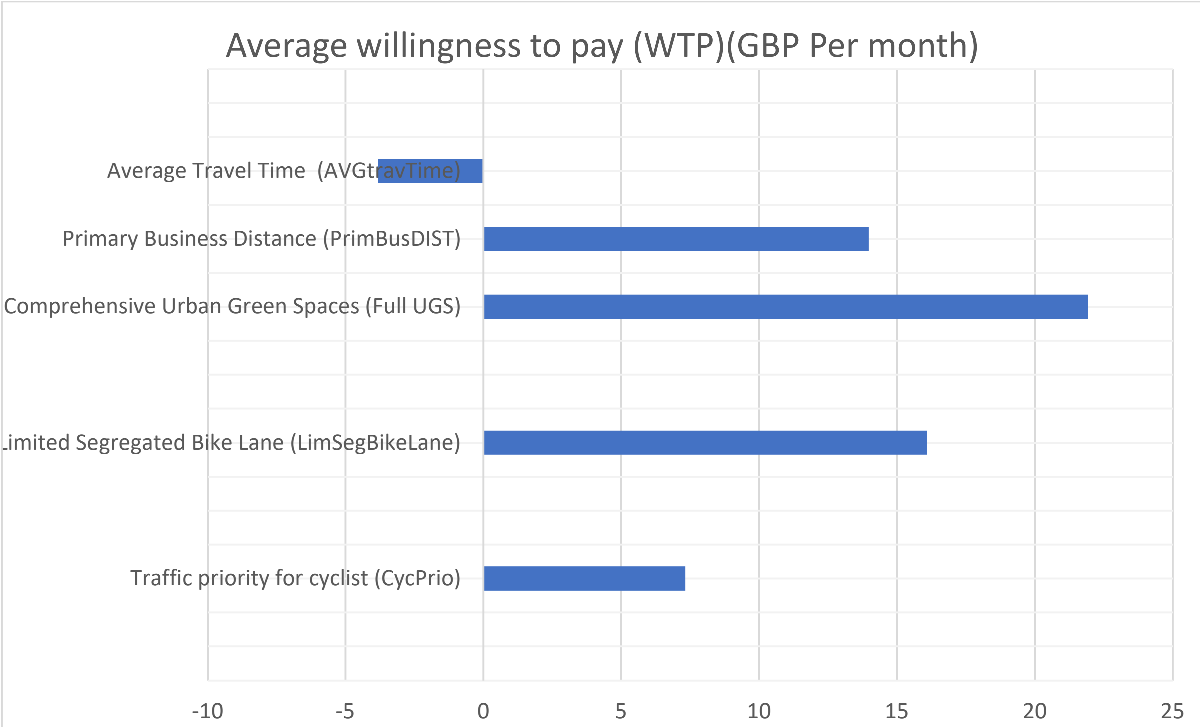
Like many research using online voluntary surveys method, Rebecca Anne Dobra *et al.* (2021) and numerous researchers have identified the sources of bias as unavoidable, from selection bias and information bias due to the explanation of complex information and hypothetical settings to the differences between stated and real-world preferences. These potential biases may not be mitigated fully. For example, in Meginnis *et al.* (2021) paper had emphasis these biases by using Monte Carlo simulations in a standard DCE with results showing these biases can be categorised as a strategic bias as respondents respond to the survey strategically and not behaving truthfully, the result from the paper therefore does not entirely minimise the variance of the data for finding respondents true preference because respondents trying to manipulate the survey using attribute decision rule to put pressure on policymakers for a certain outcome, which is more likely to occur when the hypothetical setting does make respondents to perceived this survey as very impactful to policymaking in the real world.

Even though we acknowledge these biases and carefully designed the respondent's information section. Yet again, for this level of complications, it requires a longer time frame and a much wider range of survey participants to comprehend a multifaceted and comprehensive research outcome. Nevertheless, we can still draw untenable conclusions from the data credits to pre-DCE questions and individual status quo.

7. Discussion and Conclusion

Despite the limited statistical significance of the study, this paper is partially successful in the implementation of the Discrete Choice experiment. This method effectively elicits respondents' preferences and willingness to pay estimates for various attributes that contribute to a green city. The Random Utility Theory (RUT) and Lancaster's characteristic model serve as the foundation for this experiment, setting a benchmark for future studies. Moreover, the survey as a Stated Preference (SP) method is linked to economic theory through Lancaster's model. As Train (1986) emphasizes, the experiment's discreteness guarantees that the alternatives and preferences are finite, exhaustive, and mutually exclusive.

Figure 1: Average WTP (per month GBP) of attributes



In recognition of the results from the previous section, we identified that individuals attach the most value to urban green spaces attributes which was shown by adding up individual WTP of all attribute levels. With results shown the individual's total willingness to pay is £117.61 in addition to their current council tax level for urban green spaces improvement in their urban environment. Although the alternatives offer more attributes related to transportation, individual preferences tend to lean towards UGS over other attributes due to their perception and awareness of the Green City Concept as a whole, besides all the benefits UGS may provide to individuals. Overall, the survey participants, irrespective of their backgrounds and living conditions, tend to value less on the average journey time. It is highly likely that the reason for this is the majority of the respondents are university students who primarily reside on campus. As a result, their valuations regarding travel time become significantly lower.

On the other hand, the WTP for distance to primary businesses is -£11.95 on average. Intriguingly, this means an individual is willing to accept £11.95 for every two miles increase to primary businesses, which potentially implies that individuals are willing to accept a lower tax burden for having more convenience and accessibility to these businesses. This correlation defies our expectation that individuals value the accessibility and convenience of being close to primary businesses, one possible reason might be due to increasing noise pollution and traffic volume to their settlement as these businesses often attract more traffic which can lead to congestion hence increase noise level which can be disruptive for local residents (King, 2022), while external factors such as safety concerns and reduce privacy also explain for this correlation.

In terms of traffic priority, we observed individuals place a high WTP on giving traffic priority to pedestrians over cyclists, with the respective amount of £6.26 and £29.36, around 4.7 times more than giving priority to cyclists. There may be several reasons why this difference in WTP exists, suchlike pedestrians may be seen as more vulnerable road users compared to cyclists, thus requiring more measures and infrastructures like pedestrian zones and priority for pedestrians to accommodate the vulnerability issue. In fact, around 33% of respondents stated that their mode of transportation for commuting is on foot, compared to only 4% of respondents travelling on a cycle. Indicate this result may be influenced by the demographic characteristic of the respondents, who said it could be that individuals gained more utility from enjoying a no-disturbance walking experience to commute rather than cycling.

Overseeing these WTP values, the results show respondents have a higher willingness to pay for an intermediate level of environmental improvement rather than a full-scale improvement. Whereby respondents show a higher willingness to pay towards higher-level bike lane segregation improvement. Positively this implies individuals are less willing about the changes in council tax being too much if a full-scale improvement takes place. In contrast, the same population have a higher tendency for a full-scale improvement in transportation instead. However, the total WTP on UGS is higher than the total WTP on transportation, implying respondents preferred UGS improvement to take place prior to transportation improvement.

Summarise discussions in the introduction and limitations, perceptions of individuals on the green city concept may vary by the amount of awareness that is determined by education and the level of implementation of green city-related policies, the negative outcome of lack of awareness on green city concept can cause the respondent less engaging in these policies hence attach less value to the concept as a whole. Raising public awareness becomes necessary when it comes to the concept of green cities. It is crucial that the population recognize the immense value of green cities and become more engaged towards policy implementation. Additionally, increasing government awareness is as imperative to ensure that the necessary actions are taken within tight time constraints to tackle the climate change problem.

Meanwhile, the value of WTP needs to represent the performances or the effectiveness of these attributes of a green city that can bring to environmental change. Rather, it shows the value attached to each attribute and the preferences of individuals. The government may not necessarily regard individuals' preferences as an absolute factor when implementing a new policy aside from the cost factors. In contrast, they would also consider the effectiveness of these policy instruments on the environment or the economy itself, where the public may have less insight. This situation often happens to non-market goods and public goods-related policy implementation because the public often lacks information on the long-term impacts and misses pieces of information on the potential impacts of other perspectives, which might cause by the efforts and level of expertise involved in understanding the information, the result of this can be shown by the significant gap in WTP between UGS and transportation-related attributes.

Generally, the individual decision-making process comes with a wide range of factors, both observable and non-observable. Through discrete choice experiments, it is possible to identify some of these factors and the magnitude of influence they have in the form of WTP. Specifically, the study utilized conditional and mixed logit models to observe variations to conclude the heterogeneity effect is the differences in decision-making behaviour due to respondents' sociodemographics. It is worth noting that the mixed logit model effectively takes into consideration heterogeneity effects. It is strongly recommended that future research also adopt a balanced approach by carefully weighing the pros and cons of each method for optimal results. Like past literature, this paper notes the importance of urban green spaces in the green city concept. Researchers and city planners can accurately determine the value of the green city concept by assessing the WTP value of each attribute. This knowledge is vital in identifying the most critical characteristics of a green city. Further research is necessary to explore the impact of wealth on people's preferences for the green city concept with a bootstrapping method to validate the hypothetical assumption. This information would be valuable for city planners to understand the potential effect of green gentrification on urban areas.

Overall, the results presented provide policymakers with accessible and comprehensible policy-related information for them to prioritise resource allocation upon attribute people cherish the most to be effective and cost-efficient, which is known as informed decision-making. Additionally, this attribute valuation technique can be applied to any urban area or new city plan, facilitating informed decision-making processes. Thus, this is why DCE is so effective in understanding the WTP on environmental goods regardless of the number of attributes or levels the choice sets contain.

Ultimately, this paper can serve as a pilot framework for future research by applying these methods in their research on the topic of valuing non-market goods and services. Specifically, this can be achieved by implementing a more efficient full factorial design used in this paper with a larger and more diverse survey population to elicit more statistically significant results.

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Appendix 1: Full Regression Results

Table 2: Conditional Logit Model (CLM) results

Choice	Coefficient	Robust std. err.	z	P>|z|	[95% conf.	interval]
Altern						
PedPrio	-.1386501	.2202252	-0.63	0.529	-.5702834	.2929833
CycPrio	.0295667	.180734	0.16	0.870	-.3246655	.3837989
FullUGS	.0885284	.1781469	0.50	0.619	-.2606331	.4376899
LimUGS	.4669067	.2313003	2.02	0.044	.0135665	.920247
PrimBusDIST	.0564206	.0481381	1.17	0.241	-.0379283	.1507695
CouncilTax	-.0047223	.004116	-1.15	0.251	-.0127894	.0033449
AVGtravTime	-.015406	.046248	-0.33	0.739	-.1060504	.0752384
FullSegBikeLane	-.1464082	.1912983	-0.77	0.444	-.5213459	.2285295
LimSegBikeLane	.0649932	.2127462	0.31	0.760	-.3519816	.4819681
1						
livinginurbanenvironment	-.0874408	.8538233	-0.10	0.918	-1.760904	1.586022
agegroup	-2.618429	.8527064	-3.07	0.002	-4.289702	-.9471549
education	-.1842285	1.457119	-0.13	0.899	-3.04013	2.671673
gender	-.0143675	.5855526	-0.02	0.980	-1.162029	1.133295
student	.757212	.653931	1.16	0.247	-.5244691	2.038893
EmployedFT	.0994854	2.439113	0.04	0.967	-4.681089	4.880059
currentincome	.7727917	.3725715	2.07	0.038	.0425649	1.503018
homeowner	3.170097	2.451546	1.29	0.196	-1.634845	7.975039
averagejourneytimeminutes	-.0143591	.0193007	-0.74	0.457	-.0521878	.0234696
Car	1.721149	2.724308	0.63	0.528	-3.618397	7.060694
Bus	4.09677	3.010592	1.36	0.174	-1.803882	9.997421
Walk	1.61538	2.556498	0.63	0.527	-3.395265	6.626025
Train	-1.878606	1.294031	-1.45	0.147	-4.41486	.657649
Cycle	23.07712	7.183618	3.21	0.001	8.997491	37.15675
CurrentCouncilTax	-.0033998	.0042935	-0.79	0.428	-.011815	.0050154
PrimBusDistance	-.4720839	.1365894	-3.46	0.001	-.7397942	-.2043737
_cons	2.49144	6.445915	0.39	0.699	-10.14232	15.1252
2						
livinginurbanenvironment	-.2047047	1.215037	-0.17	0.866	-2.586134	2.176725
agegroup	-2.242103	1.001207	-2.24	0.025	-4.204433	-.2797726
education	.0390149	1.592378	0.02	0.980	-3.081988	3.160018
gender	-.4088603	.6824647	-0.60	0.549	-1.746467	.9287461
student	1.043965	.8975626	1.16	0.245	-.7152256	2.803155
EmployedFT	2.617927	2.835589	0.92	0.356	-2.939724	8.175579
currentincome	.4092577	.4320698	0.95	0.344	-.4375836	1.256099
homeowner	3.018865	1.785191	1.69	0.091	-.4800447	6.517775
averagejourneytimeminutes	.0073179	.0246571	0.30	0.767	-.041009	.0556449
Car	1.897365	2.255974	0.84	0.400	-2.524262	6.318993
Bus	4.978963	2.738546	1.82	0.069	-.3884891	10.34642
Walk	2.316666	2.59872	0.89	0.373	-2.776732	7.410065
Train	-1.639323	.7775226	-2.11	0.035	-3.163239	-.1154068
Cycle	23.41335	8.115277	2.89	0.004	7.507703	39.31901
CurrentCouncilTax	-.0059725	.0054182	-1.10	0.270	-.0165921	.004647
PrimBusDistance	-.385579	.1707085	-2.26	0.024	-.7201616	-.0509965
_cons	.4002098	7.735443	0.05	0.959	-14.76098	15.5614
3	(base alternative)					

Table 3: Mixed Logit Model (XLM) results

Choice	Coefficient	Robust std. err.	z	P>|z|	[95% conf.	interval]
Altern						
PedPrio	-.1386714	.2202227	-0.63	0.529	-.5703	.2929573
CycPrio	.0295777	.1807286	0.16	0.870	-.3246438	.3837992
FullUGS	.0885315	.1781432	0.50	0.619	-.2606228	.4376857
LimUGS	.4669904	.2312932	2.02	0.043	.013664	.9203168
PrimBusDIST	.0564239	.0481367	1.17	0.241	-.0379222	.1507701
CouncilTax	-.0047231	.0041158	-1.15	0.251	-.0127898	.0033437
AVGtravTime	-.0154052	.0462461	-0.33	0.739	-.1060459	.0752355
FullSegBikeLane	-.1464231	.1912923	-0.77	0.444	-.5213492	.228503
LimSegBikeLane	.0649695	.2127425	0.31	0.760	-.3519981	.4819371
1						
livinginurbanenvironment	-.0873715	.8538553	-0.10	0.918	-1.760897	1.586154
agegroup	-2.619139	.8528038	-3.07	0.002	-4.290603	-.9476738
education	-.1831275	1.457259	-0.13	0.900	-3.039302	2.673048
male	-.0142445	.5855868	-0.02	0.981	-1.161974	1.133485
student	.7575234	.6540625	1.16	0.247	-.5244155	2.039462
EmployedFT	.098178	2.439039	0.04	0.968	-4.682251	4.878607
currentincome	.7729556	.372614	2.07	0.038	.0426456	1.503266
homeowner	3.172029	2.451832	1.29	0.196	-1.633474	7.977532
averagejourneytimeminutes	-.0143571	.0193004	-0.74	0.457	-.0521851	.0234709
Car	1.720956	2.723934	0.63	0.528	-3.617857	7.05977
Bus	4.096746	3.010304	1.36	0.174	-1.803342	9.996834
Walk	1.615159	2.556139	0.63	0.527	-3.394781	6.625099
Cycle	24.45907	7.184115	3.40	0.001	10.37846	38.53968
Train	-1.877922	1.29405	-1.45	0.147	-4.414214	.6583692
CurrentCouncilTax	-.0034022	.0042938	-0.79	0.428	-.0118179	.0050135
PrimBusDistance	-.4721649	.136603	-3.46	0.001	-.7399019	-.2044279
_cons	2.487694	6.44622	0.39	0.700	-10.14667	15.12205
2						
livinginurbanenvironment	-.204628	1.215059	-0.17	0.866	-2.5861	2.176844
agegroup	-2.242881	1.001296	-2.24	0.025	-4.205385	-.2803763
education	.0403668	1.592528	0.03	0.980	-3.08093	3.161664
male	-.4086699	.6824819	-0.60	0.549	-1.74631	.9289701
student	1.044352	.8976581	1.16	0.245	-.715026	2.803729
EmployedFT	2.61661	2.835362	0.92	0.356	-2.940597	8.173818
currentincome	.4094701	.4321028	0.95	0.343	-.4374359	1.256376
homeowner	3.020888	1.785568	1.69	0.091	-.4787616	6.520538
averagejourneytimeminutes	.0073194	.0246562	0.30	0.767	-.0410059	.0556447
Car	1.897463	2.255778	0.84	0.400	-2.523779	6.318706
Bus	4.979099	2.738446	1.82	0.069	-.3881565	10.34635
Walk	2.316681	2.598536	0.89	0.373	-2.776355	7.409718
Cycle	24.7952	8.116248	3.06	0.002	8.887646	40.70275
Train	-1.638467	.7776283	-2.11	0.035	-3.16259	-.1143436
CurrentCouncilTax	-.005976	.0054185	-1.10	0.270	-.0165961	.0046441
PrimBusDistance	-.3856915	.1707194	-2.26	0.024	-.7202954	-.0510876
_cons	.3952676	7.735928	0.05	0.959	-14.76687	15.55741
3	(base alternative)					

Table 6: Conditional Logit Model (CLM) with no interaction variables results

Choice	Coefficient	Robust std. err.	z	P>|z|	[95% conf.	interval]
Altern						
PedPrio	-.2162937	.2308171	-0.94	0.349	-.6686869	.2360994
CycPrio	.0777377	.1773397	0.44	0.661	-.2698416	.4253171
FullUGS	.1192057	.2296625	0.52	0.604	-.3309246	.569336
LimitUGS	.338001	.2145473	1.58	0.115	-.082504	.7585059
PrimBusDIST	.040045	.0483075	0.83	0.407	-.054636	.1347261
CouncilTax	-.0034911	.003833	-0.91	0.362	-.0110036	.0040215
AVGTravTime	.0042115	.007195	0.59	0.558	-.0098904	.0183135
FullSegBikeLane	-.1194819	.2214574	-0.54	0.590	-.5535305	.3145667
LimSegBikeLane	.0336116	.1878764	0.18	0.858	-.3346194	.4018427
1	(base alternative)					
2						
NorminalCouncilTax	.0027755	.0016901	1.64	0.101	-.0005371	.006088
EvenBirthday	-.3932696	.2700611	-1.46	0.145	-.9225796	.1360405
_cons	-.1497139	.2132088	-0.70	0.483	-.5675954	.2681677
3						
NorminalCouncilTax	.0023584	.0025822	0.91	0.361	-.0027026	.0074194
EvenBirthday	-.9391246	.4952474	-1.90	0.058	-1.909792	.0315424
_cons	-.1608935	.4559188	-0.35	0.724	-1.054478	.732691

Appendix 2: Full list of attributes and levels

Availability of Non-Motorised Traffic Routes

- No segregated bike lanes nor the pedestrian zones
- Limited segregated bike lanes and pedestrian zones
- Segregated bike lanes with pedestrian zones

Average travel time change

- -20%
- No changes
- +20%

Council tax change

- -20%
- -10%
- No changes
- +10%
- +20%

Distance to primary businesses – Respondent’s distance to daily businesses stores (supermarket, post office etc.)

- 2 miles closer
- No changes
- 2 miles further

Availability of Urban Green Spaces (UGS)

- No parks nor on street green spaces
- Limited parks and on-street green spaces
- Large parks with no on-street green spaces
- Large parks with on-street green spaces

Traffic Priority – Who is prioritised in the city design?

- Motor traffic
- Cyclist
- Pedestrian

Appendix 2: Respondent-related questions full list

- Age group
- Average journey time to work or school
- Current income bracket per month
- Council tax bracket per month
- Coming from the UK
- Currently live in an urban environment
- Distance to primary businesses (supermarket, post office etc.)
- Education status
- Gender
- Is a homeowner
- Method of transportation to commute