Investigating the Determinants of Mode Choice for Demand-Responsive Transportation in Car-Dependent Peri-Urban Areas

Abstract

Traditional public transit is often inefficient to operate in peri-urban areas due to their low population density. As a result, these areas are often deeply car-dependent. Demand-Responsive Transportation (DRT) has been proposed as a car alternative in peri-urban areas. DRT combines the pooled rides of public transit with the flexibility of a taxi, making it theoretically more efficient than traditional transit in peri-urban areas. However, DRT systems fail regularly in practice because they are not tailored to the preferences of their users. This study investigates trip- and individual-level determinants of DRT uptake among peri-urban drivers. A stated preference survey was conducted asking drivers in Dublin's commuter belt about their intentions to use a hypothetical DRT offering. The results indicate that drivers show intention to use DRT for commuting and leisure trips, but usually only at trip distances of at least 10 km. Regression models were developed to measure the impact of both socio-demographic and social-psychological characteristics on DRT intentions. In addition, a measure of individual car dependency was developed using latent class analysis, and regression models were also used to determine the level of constraint on DRT intentions imposed by car dependency. Ultimately, these findings broaden what is known about the trip- and individual-level determinants of DRT intentions among drivers, in particular highlighting the role of social-psychological factors.

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1. Introduction

Despite the well-documented aggregate negative impacts of extensive car use on health, the environment, and the economy, car use remains widespread across the European Union. Cars are more damaging to the environment, more dangerous to use, and less spatially efficient than public transportation (PT) (Saeidizand et al., 2022). Cities can make efficient use of PT to provide a viable alternative to personal car use. However, the peri-urban areas around cities often struggle to provision PT in an economically efficient manner due to their lower population density (Martí et al., 2023). Previous research has found that the peripheral areas around cities tend to face higher levels of car dependency than urban areas, meaning non-use of cars in these areas is associated with high levels of economic and social marginalization (Mattioli, 2014). So in addition to the health, environmental, and economic downsides of widespread car usage, the lack of viable car alternatives in peri-urban areas contributes to social inequity.

Demand-Responsive Transportation (DRT) has been proposed as a more feasible car alternative for peri-urban areas than traditional PT (Schasché et al., 2022). DRT refers to an on-demand transportation system that operates somewhere between a taxi and a bus: passengers request rides, and the transport provider generates routes and schedules that allow them to provide trips for multiple passengers simultaneously. In other words, DRT combines the flexibility of a taxi or ride-hailing service with the cost-efficiency and environmental benefits of PT.

Previous research has found that DRT's responsiveness to the spatial and temporal distribution of trip demand makes it theoretically more cost-efficient to run in peri-urban areas than traditional PT (Mortazavi et al., 2024), but establishing peri-urban DRT has proven difficult. DRT systems routinely fail in practice. Half of DRT systems do not survive past seven years of operation (Currie & Fournier, 2020). DRT systems have very high startup costs and often rely on some level of government subsidy, which limits their long-term sustainability (Enoch et al., 2006). This is especially true for peri-urban DRT, which has relatively lower demand than urban DRT (Martí et al., 2023). These systems must quickly adopt new users in order to become economically sustainable (Martí et al., 2023).

Adaptability to users has long been established as the number one factor determining success in DRT systems (Bellini et al., 2003). Operators must tailor DRT systems to the preferences of their intended users to ensure that intended DRT use turns into actual DRT travel behavior. Unfortunately, little is known about user preferences towards DRT in peri-urban areas, such as the types of trips for which people are most willing to use DRT and the role of personal attitudes in determining DRT use. Additionally, the extent to which an individual's level of car dependency constrains their intention to use DRT has not been established, which is a particularly important consideration for establishing DRT in peri-urban areas. A greater understanding of the trip- and individual-level determinants of intentions to use DRT in

car-dependent peri-urban areas would help DRT operators tailor their services to users, thereby reducing the risk of system failure.

This thesis investigates the following question: What are the key determinants of intention to use DRT among drivers in car-dependent peri-urban areas? It addresses gaps in current knowledge about DRT by asking the following sub-questions: First, for what kind of trips are drivers in car-dependent peri-urban areas willing to use DRT instead of their current form of transportation? Second, what are the socio-demographic and attitudinal determinants of DRT intentions among drivers in car-dependent areas? And finally, does an individual's level of car dependency constrain their intention to use DRT? To answer these questions, a survey was conducted among car users in the commuter belt of Dublin, Ireland which asked about their intentions regarding use of a hypothetical DRT system. This thesis discusses the results of this survey and potential takeaways for transport operators seeking to fine-tune a DRT service in a context of peri-urban car dependency.

Dublin's commuter belt was selected for study because it serves as a representative example of car-dependent peri-urban sprawl. It is a growing, low-density area where having access to a car is nearly required for commuting (Carroll et al., 2017). Like many peri-urban areas, Dublin's commuter belt struggles to provision PT efficiently. Traditional PT offerings in the area are limited and have not kept up with population growth (Mayor et al., 2012). As a result, household car ownership rates in the commuter belt hover around 90% (Central Statistics Office, 2022b). This region, and other car-dependent peri-urban areas like it, could benefit greatly from the introduction of a viable car alternative like DRT, so knowledge of how to tailor DRT for success in these areas is particularly valuable.

The thesis is organized into six sections. Section 1 has introduced the difficulty of combatting car dependency in lower-density areas and the possibilities and challenges offered by DRT, as well as gaps in our current understanding of potential DRT users. Section 2 establishes the theoretical framework used to analyze intended DRT use and introduces relevant literature on DRT intentions and car dependency. Section 3 explains the survey methodology and data analysis techniques used in this thesis. Section 4 states the results of the survey, while section 5 evaluates these results in the context of other relevant transportation literature. Section 6 asserts the key policy takeaways of the thesis, its methodological limitations, and possible directions for future research.

2. Literature Review

2.1 The Three Levels of Mode Choice Determinants

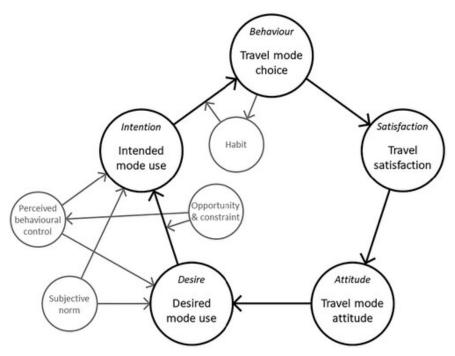
The determinants of travel mode behavior can be said to operate at three distinct levels: the built environment, the traveler, and the individual trip (Jeong et al., 2022). In this section, some of the key variables relating to mode choice at each level will be discussed. In the following section, these levels and variables will be connected to existing research on DRT.

The first and most broad level is the built environment. Characteristics of the built environment such as density, land-use, and road design have been shown to affect travel mode choice (Jeong et al., 2022). Several studies have reaffirmed that population density, walkability, and mixed land-use are positively correlated with traditional PT mode choice (Yu et al., 2023). Variables at the level of the built environment are well-established in the DRT literature and therefore not analyzed in this study to the extent of traveler- and trip-level variables. However, distance to the nearest PT stop is incorporated into the measurement of respondent car dependency, as described in section 4.3.

Mode choice is also affected by factors at the level of the individual traveler. Socio-demographic factors such as age, gender, and income level have been found to be significant predictors of mode choice (Jeong et al., 2022). Additionally, contributions to transportation research from social psychology have shown that various factors under the umbrella of "user preferences," such as desires, attitudes, and beliefs, play key roles in determining travel mode choice (Gärling & Fujii, 2009). The Travel Mode Choice Cycle (TMCC) provides a well-supported framework for breaking down the influence of user preferences on mode choice. The TMCC analyzes travel mode choice as an interrelated cycle of behavior, satisfaction, attitudes, desires, and intentions. In other words, travel behavior influences travel satisfaction, which influences attitudes, and so on in a cyclical manner that circles back to travel behavior (see Figure 1) (De Vos et al., 2022).

Figure 1

The Travel Mode Choice Cycle



Note. From De Vos et al. (2022). Used under Creative Commons license CC BY-NC-ND 4.0.

Within the TMCC, travel mode attitude refers to (un)favorable appraisals of a travel mode, while desired mode use captures the desire to use a mode of transportation, regardless of opportunities and constraints that may impact an individual's travel mode choice (De Vos et al., 2022). Attitudes unrelated to the specific travel mode can also impact mode choice. For example, pro-environmental attitudes have been found to increase desire and intention for PT (Bouscasse et al., 2018).

Intended mode use refers to the planned or expected use of a particular travel mode (De Vos et al., 2022). In the context of the current study, "DRT intentions" refers to people's intentions to use DRT and is measured directly by a stated preference survey (described further in section 3.2). In addition to the main concepts of attitude and desire, intention is influenced by perceived behavioral control, or the extent to which one believes they can use a mode of transportation with ease, as well as subjective norms, or perceptions about how others will react to one's travel mode use (De Vos et al., 2022). Opportunity and constraint also impact intended mode use by either enabling or hindering the translation of desires about certain travel modes into intentions to use certain travel modes. Indicators of car dependency, such as a lack of access to car alternatives and high average trip distances, often function as constraints on non-car travel modes (De Vos et al., 2022). Behavior and Satisfaction are less relevant to the present research because

there is no actual widespread DRT system in the study area from which behavior and satisfaction could be measured.

The final and most specific level of travel mode determinants is that of the individual trip. Factors such as trip distance and trip purpose impact the mode of travel that people decide to use. For example, commuting trips tend to be more sensitive to travel time unreliability than leisure or shopping trips, so people are more inclined to choose travel modes with high travel time reliability for commuting trips than for other types of trips (Gim, 2018, G. Zhang et al., 2024). As described below in section 3.2, trip-level variables are included in the collection of data on DRT intentions in the survey used in this thesis.

2.2 Demand-Responsive Transportation

The influence of the built environment on DRT mode choice is the best-studied of the three levels of mode choice determinants. Multiple studies have shown that DRT can be an attractive mode choice in a variety of low-density, peri-urban environments. A simulation study of an integrated DRT system in the suburban district of Belconnen in Canberra, Australia found that the DRT outperformed traditional PT in several key metrics (Mortazavi et al., 2024). In the simulation, DRT was more cost-effective and less environmentally harmful than the existing PT network, as well as offering shorter trip times for passengers and a more equitable distribution of excess travel times (Mortazavi et al., 2024). The findings of this simulation study are in line with previous simulation studies that have found DRT to be an effective solution for areas in rural Denmark (Dytckov et al., 2022), an area of scattered villages and cities in Germany (Lu et al., 2023), and an area containing "dead-end villages" in Hungary (Lakatos et al., 2020).

Previous studies have examined the influence of socio-demographic characteristics on DRT intentions, but their findings reveal discrepancies. Within the context of a mobility-as-a-service (MaaS) scheme proposed to urban residents in Amsterdam, Alonso-Gonzáles et al. (2017) found that higher educated, working young adults were more likely to have DRT intentions than their less educated, retired, and older counterparts. On the other hand, a simulation study across ten metropolitan areas in the United States found that DRT intentions were highest among both respondents aged 18–24 and respondents aged 50–54, as well as a positive association between middle income levels and DRT intentions (Asgari & Jin, 2020). Other studies have found DRT intentions to be highest among elderly and low-income groups (Schasché et al., 2022). In general, the influence of socio-demographic variables on DRT intentions is inconsistent. This may point to other factors, such as socio-psychological variables, being more important in determining DRT intentions at the level of the individual.

Despite the fact that the influences of built environment and socio-demographic variables on DRT intentions have previously been studied, many DRT systems still fail to find a user base. As of 2020, fully half of DRT systems last less than 7 years, with the United Kingdom, for example,

sporting an overall failure rate of 67% (Currie & Fournier, 2020). There are many potential explanations for this trend, but the basic reality is that DRT operators often lack a good understanding of the market they are trying to serve (Enoch et al., 2006). In order to achieve the theoretical benefits posited by simulation studies and serve as a viable car alternative in peri-urban areas, more needs to be known about the attitudes, desires, and constraints that underlie people's intentions to (not) use DRT.

Previous DRT research has largely avoided the social-psychological approach to understanding individual mode choice in favor of examining willingness-to-pay and cost-time tradeoffs (Schasché et al., 2022). As a result, little is known about the role of attitude, desire, perceived behavioral control, and constraints in influencing DRT mode choice. The only well-established attitudinal finding regarding DRT is that the need to share rides with other passengers is a less significant consideration for potential DRT users than other factors. A study of citydwellers in the Netherlands found that the tradeoff between trip time and cost was a more important factor in determining travelers' willingness to use DRT than the disutility associated with sharing a ride (Alonso-González et al., 2021). This finding is in line with both DRT simulation studies and studies of actual DRT users conducted in the United States (Lavieri & Bhat, 2019; Sarriera et al., 2017) and Switzerland (Stoiber et al., 2019). In short, a user's feelings towards shared rides is generally not a strong determinant of their willingness to use DRT. The role of other attitudes in determining DRT intentions, such as environmental attitudes and attitudes towards DRT itself, as well as the impact of perceived behavioral control and constraints, have not been established in the existing literature and will be examined in the present study.

The role that trip-level characteristics play in DRT intentions is similarly murky. A study of DRT intentions in the Northern Beaches area of Sydney, Australia utilized a latent class choice model to segment survey respondents into two groups: group one, who had a high uptake of DRT (96 percent), was more likely to include people making work-related trips by car, whereas group two, who had a much lower DRT uptake (44 percent), was more likely to use cars for non-work trips such as shopping and socializing (Saxena et al., 2020). This indicates that people who drive to work or school are more likely to demonstrate interest in DRT than drivers performing other types of trips. However, this study did not directly ask drivers how they intended to use DRT service, so the relationship between trip purpose and DRT intentions established in this study is somewhat indirect. The present study builds on this finding by directly asking drivers about DRT intentions for various trip types, including commuting and leisure trips but also grocery shopping and doctor's appointment trips.

Detailed information about users and trips can be used to tailor several aspects of DRT offerings. DRT operators have to make many choices in deciding how a DRT system will operate, such as which area to serve, how many vehicles to purchase, and how flexible the service should be. At their least flexible, DRT systems can operate basically on the same principles as a traditional bus

route, with fixed schedules and a fixed route that may change infrequently based on demand. At the other extreme of the spectrum, a DRT system can run as a sometimes-shared taxi service solely offering door-to-door transportation. More flexible services are more complex for operators to run. Historically, more complex DRT systems are more likely to fail than their less-flexible counterparts (Currie & Fournier, 2020). Theoretically, then, the ideal configuration of a DRT system is the one that minimizes system complexity while still meeting the desires of its users (Enoch et al., 2006). A greater understanding of the trip- and individual-level determinants of DRT intentions is needed to help operators find this balance and improve the chance of long-term DRT system success.

2.3 Car Dependency

The reason for focusing on DRT in the present thesis is that it is theoretically a more viable car alternative in peri-urban areas than traditional PT. Because peri-urban areas often suffer from car dependency, this means DRT is uniquely well-positioned to combat car dependency compared to other forms of shared transportation. This section further defines car dependence, explains some of the harms it causes, and examines the link between car dependency and peri-urban areas.

Car dependency refers to a situation in which an individual's willing or unwilling non-use of cars has (or would have) a significant negative impact on their well-being (Jeekel, 2016). This situation arises from both individual and structural forces. An individual's preference for driving over other forms of transportation, the design of the built environment, the distance at which individuals are willing to commute for work, and the viability of other forms of transportation, among many other factors, all contribute to car dependency (Goodwin, 1995). Importantly, these structural and individual factors are self-reinforcing. As cars become a more desirable alternative to PT or active mobility, the built environment and transportation system change to better accommodate cars, and vice-versa (Wegener & Fuerst, 2004).

This cycle leads to negative outcomes for drivers and non-drivers alike. Commonly cited areas of negative externalities include traffic (longer travel times and earlier departure times for commutes), the global environment (climate change from greenhouse gasses, ground and water acidification), the local environment (air and noise pollution), and safety (death and injury due to road traffic accidents) (Saeidizand et al., 2022). Car dependency also has harmful outcomes for the structure of urban development by encouraging urban sprawl, which promotes inactive lifestyles and functionally segregated areas (Gerten & Fina, 2022).

Car dependency also reinforces social inequity. Researchers Giulio Mattioli and Matteo Colleoni (2016) developed a four-part typology of car-related transport disadvantage in car dependent areas. The first is Car Deprivation. For people who do not have access to a car, either because they cannot afford one or because they are unable to drive, living in a car-dependent area can result in a "lack of access to services, opportunities and social networks" (Mattioli & Colleoni,

2016, p. 176). People who do have a car may face Car-Related Economic Stress (CRES), wherein the economic burden of owning and operating a personal vehicle affects spending in other essential areas, which negatively impacts well-being and social inclusion. The third transport disadvantage, Oil Vulnerability, highlights that rises in fuel and energy costs may cause even more people in car-dependent places to experience CRES in the future. Finally, car-dependent places encourage Car-Related Time Poverty, wherein the time one spends traveling by car results in social exclusion. Socially and/or economically vulnerable populations are more likely to bear the negative outcomes of car dependency.

Car dependency is usually heightened in peri-urban regions compared to cities. This can be seen when comparing people who live without cars in cities to people who live without cars in the peripheries of those urban centers. In Britain, for example, one study found that carless households in peripheral areas were much more likely to be in a marginal socio-demographic situation than their urban counterparts (Mattioli, 2014). In other words, car-free households in urban areas did not face car deprivation like their peri-urban peers. More generally, cities in Western Europe, North America, and Australia tend to feature diminishing rates of walking, cycling, and public transport use as distance to the city center increases (Buehler et al., 2017). As such, there is an acute need for viable alternatives to private car use in peri-urban peripheries.

Previous research has identified possible ways to reduce car dependency in peri-urban areas. One study utilized a stated preference survey to compare the impacts of an incentives-only approach to encouraging car-sharing and carpooling in the Greater Dublin Area. It found that car alternatives could be made viable through the introduction of policies that reduce costs and travel times for non-private vehicles, such as the proliferation of carpool lanes and free parking for shared car users (Carroll et al., 2017). Socio-demographic and built environment factors were also found to be significantly correlated with willingness to use incentivized car-sharing and carpooling, with women, people in higher age cohorts, people with higher levels of education, and people living in peripheral areas being more likely to use these modes (Carroll et al., 2017). That study took an incentives-only approach to reducing car dependency, under the assumption that disincentives towards car use in an area lacking viable car alternatives would only further entrench the inequity caused by car deprivation (Carroll et al., 2017). However, further research has questioned the efficacy of strategies to reduce car dependence that avoid disincentives towards driving. Research utilizing a choice model incorporating car, PT, and active mobility modes found that, although policy incentives could encourage a modal shift away from individual car use, incentives alone would not be enough to bring about a radical change in travel behaviors (Carroll et al., 2021). In other words, the presence of competitive car alternatives is a prerequisite to making substantial progress against car dependence. Therefore, a DRT system not only contributes to reducing car dependence by providing people with another option for how to travel, but also by opening the possibility for policymakers to deploy disincentives towards driving without excessively harming already disadvantaged car-deprived groups.

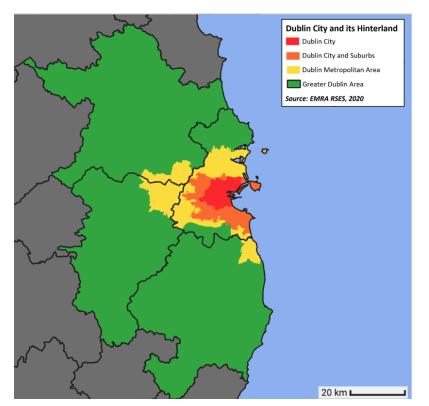
3. Methodology

3.1 Case Study Context: Dublin's Commuter Belt

Spanning the counties of Fingal, Meath, Kildare, and Wicklow in the east of the Republic of Ireland, Dublin's commuter belt encompasses the towns and rural areas around Dublin from which residents commonly commute to the city (see Figure 2). The commuter belt is a product of the 'Celtic Tiger' period in the 1990s, during which Ireland saw unprecedented rates of economic growth (Bartley & Kitchin, 2007). This growth led to unprecedented demand for housing in and around Dublin. Even with a 200 percent increase in new home building, the city was unable to keep up with demand, and residents began spilling over into the rural hinterland of Dublin (Gkartzios & Scott, 2010). A network of motorways leading into the city enabled these new peri-urban residents to commute to the city with relative ease by car.

Figure 2

Dublin and Its Hinterland



Note. For this study, the yellow and green areas make up the commuter belt. Adapted from Jacobfrid. (2020). Used under Creative Commons license CC BY-SA 4.0.

Population density in the commuter belt is sporadic, characterized by towns of about 10,000 to 40,000 people surrounded by rural farmland. Within towns, most people live in housing estates usually consisting of semi-detached or single-family detached homes. Street networks within these estates emphasize cul-de-sacs and circuitous routes, which allow for a greater number of homes to be built at the expense of transport connectivity and ease of access (see Figure 3). Sidewalks are common, though not always present, and dedicated bike infrastructure within estates is rare.

Figure 3



A Typical Road Network in Ratoath, Ireland

Note. Imagery ©2024 Airbus, Maxar Technologies, Map data ©2024 Google.

Car-Related Economic Stress and Car-Related Time Poverty are both common in the commuter belt. Although income levels in the commuter belt are higher than in many other regions in Ireland, this is more than offset by the cost of commuting in the region (Vega et al., 2017). A large portion of the cost of car commuting in this area is time cost. The counties comprising the commuter belt have some of the highest average commute times in the country, with County Meath topping the list (Central Statistics Office, 2023). 19% of Co. Meath residents have a commute time of over one hour, compared to 11% nationwide (Central Statistics Office, 2023).

Traditional PT does exist in the commuter belt, though their viability as an alternative to car use depends on route and time of day. The growth of PT networks in the commuter belt has overall lagged behind population growth (Mayor et al., 2012). Commuter rail services extend to some, but not all, of the commuter towns in the area. Bus routes connect all the major commuter towns to Dublin, but service is infrequent outside of peak commuting times. PT trips not oriented towards or away from Dublin are often inconvenient and circuitous as the system focuses on serving trips to and from Dublin.

A variety of non-PT car alternatives exist as well, with varying degrees of uptake. Car-sharing providers GoCar and Yuko both operate in the commuter belt, though not all commuter belt towns have access to car-sharing facilities. On-demand ride-hailing apps such as Uber have been prohibited from entering the transportation market in favor of local taxi services (Carroll et al., 2017). Aside from vehicle-based transport, active mobility has seen a boost in the commuter belt in recent years with the construction of new (sometimes protected) bike lanes in commuter towns like Ashbourne and Swords. However, cycling is still rather uncommon in Ireland generally, with a commuting mode share of only 3% in 2022 (Central Statistics Office, 2023).

The National Transport Authority has developed the "Connecting Ireland Rural Mobility Plan" in an effort to improve the distribution of private car alternatives for areas of lower population density in Ireland. The agency is focusing the bulk of its efforts on improving existing fixed bus routes and expanding the fixed bus network to new parts of the island. They have also identified DRT as an innovative and useful tool for expanding transportation options in "sparsely populated areas" (National Transport Authority, 2021, p. 5). The agency is currently piloting an app-based "Smart Demand Responsive Transport" network to serve rural areas (National Transport Authority, 2022, p. 49).

3.2 Survey Design

A stated preference (SP) survey was used to ascertain the intentions of residents in Dublin's commuter belt to use a DRT service, as well as the role of personal characteristics and car dependency in determining DRT intentions. SP techniques are a long-established tool in transportation research for evaluating and forecasting travel behavior (Pearmain et al., 1991). As opposed to revealed preference techniques, which analyze existing travel behaviors to make determinations about individuals' preferences and future behaviors, SP techniques allow researchers to predict preferences and behaviors for hypothetical travel scenarios. In the present case, an SP survey was developed based on a hypothetical DRT service operating in the study area.

A traditional modal choice SP survey presents respondents with several choice scenarios, wherein they are asked to pick between different travel modes that vary in terms of travel time,

cost, and/or other attributes. This allows researchers to weigh the relative importance that respondents place on each of these attributes in the given travel context. However, a modified SP approach was utilized in the present survey. Respondents were asked about their intention to use DRT as opposed to their current travel mode for various types of trips. For each type of trip, respondents were first asked what travel mode they use for this trip and the length (distance) of this trip. The length of the respondent's trip was then used to estimate the cost and travel time of the proposed DRT replacement. These time and cost estimates were not altered for different respondents like in a traditional SP survey, as the aim was not to determine the relative importance of time vs cost for respondents. Rather, the aim was to determine the relationship between trip- / individual-level characteristics and DRT intentions.

Plausible cost and time estimates for the hypothetical DRT service were derived from current bus fares in the study area. Based on a previous DRT simulation study, which found that operational costs for DRT were usually equal to or lower than those of the existing public transit system (Mortazavi et al., 2024), the baseline cost for DRT fares was assumed to be equal to those of a bus trip. Based on findings in that same study, in-vehicle DRT travel times were assumed to be 15–30% quicker than bus travel times (Mortazavi et al., 2024). These estimates were then tweaked to more realistically model the differences between door-to-door and stop-to-stop services. Door-to-door services were assumed to be more expensive than stop-to-stop. Stop-to-stop services were assumed to have less in-vehicle travel time due to having to make fewer deviations. Additionally, the time it takes to walk to and from stops was included in the stop-to-stop travel time. This information is summarized in Table 1, which was shown to survey respondents.

Table 1

	How it works	Likely fares per trip	Likely travel time	Walk time to / from stops
Door-to-door	Picks you up where you are, drops you off at your destination	+10% compared to a bus fare	15–20% faster than bus	0 min
Stop-to-stop	Picks you up and drops you off at the closest stop (e.g. a nearby church, school, or grocery store)	About equivalent to a bus fare	25–30% faster than bus	5–10 min

Comparison of Door-to-Door and Stop-to-Stop Services

The survey consisted of four sections. Section 1 contained questions about current travel behavior, including indicators meant to measure car dependency. In section 2, respondents were presented SP trip scenarios. Section 3 contained attitudinal questions. In keeping with previous findings regarding SP surveys, attitudinal questions were asked after the trip scenarios to avoid influencing respondents' choice behavior (Liebe et al., 2016). Section 4 covered socio-demographic questions.

In the SP trip scenarios section, respondents were presented with four trip types that could be completed with DRT: a work/school commute, a grocery shopping trip, a self-selected leisure trip (such as going out to eat, going to the cinema, going to a concert, or going to see a theater performance), and a doctor's visit. For each trip type, they indicated on a five-point Likert scale (Likert, 1932) how likely they would be to utilize either a stop-to-stop or door-to-door DRT service, from "Very Unlikely" to "Very Likely". The Likert scale was also used for the attitudinal questions in section 3. These questions were selected to measure respondents' overall dispositions towards cars, DRT, and their transportation options in general. The attitudinal statements on cars were specifically derived from a previous study measuring the impact of personal motives on car ownership and use (Soza-Parra & Cats, 2024). A copy of the entire survey distributed to respondents is attached as Appendix A.

3.3 Distribution and Sampling

The survey was distributed through two methods: via invitations delivered directly to homes in the study area and via social media. These sampling methods may have resulted in participation bias, whereby the individuals who self-selected to take the survey may not be representative of the study area population as a whole. However, given time and budgetary constraints, these methods were determined to offer the best chance of achieving an adequate sample size. Certain demographic questions were lifted verbatim from the 2022 census in order to compare the make-up of the sample to known demographic information. For reasons of privacy, all survey responses were kept anonymous and respondents were able to skip questions they did not wish to answer.

In total, 445 survey responses were recorded. 129 respondents were screened out for failing to meet one or more of the following criteria:

- Being at least 18 years old,
- Owning or having access to a car for day-to-day use, and
- Living within the Dublin commuter belt region, but outside the city of Dublin and its inner suburbs.

A further 48 responses were removed either because the respondent did not answer questions related to DRT intentions or because the respondent completed the survey in under three minutes

(median survey completion time among full responses was 8:06). 268 survey responses were included in the final analysis.

Table 2 shows characteristics of survey respondents. Nearly two-thirds of survey respondents were women (63.5%), whereas the actual regional gender breakdown is about 50/50 (Central Statistics Office, 2022a). Respondents skewed towards being over 45 years old, and most respondents were either working (73.7%) or retired (18.4%). A sizable minority of respondents (17.2%) reported having children under the age of 6 years old in their household.

Table 2

Gender		Age	
Man	92 (36.5%)	18–24	7 (2.7%)
Woman	160 (63.5%)	25–34	17 (6.6%)
Location		35–44	49 (19.1%)
Outer suburbs of Dublin	40 (14.9%)	45–54	84 (32.7%)
Commuter town	131 (48.9%)	55–64	61 (23.7%)
Elsewhere in commuter counties	97 (36.2%)	65+	39 (15.2%)
Principal Status		Young kid(s) at home? (<6 years old)
Working	188 (73.7%)	Yes	44 (17.2%)
Retired	47 (18.4%)	No	212 (82.8%)
Other	20 (7.9%)		

Aggregated Characteristics of Survey Respondents

3.4 Explanation of Data Analysis

Descriptive methods were used to analyze the impacts of trip characteristics on DRT intentions among the sample population. Following this, two sets of logit regression models were used to analyze the impact of socio-demographic and attitudinal variables on DRT intentions. Then, a latent class model was used to determine the distribution of car dependency among the sample and ordered logit models were used to analyze the impact of car dependency on DRT intentions. Several respondents skipped at least one question when filling out the survey. In order to include the full sample in the final models, missing data for predictor variables was imputed. Imputation is a statistical method that allows for all observations to be included in statistical analysis by filling in missing values with predicted responses (Austin et al., 2021). Outcome variables (i.e. stated DRT intentions) were not imputed. For numeric variables, the average value was imputed into missing cells, while the modal value was imputed for missing cells of categorical variables. These simple methods were deemed sufficient due to the low number of missing cells per imputed variable (ranging from 1 to 18 cells out of 268 responses) (Z. Zhang, 2016).

Regression models were developed to analyze the relationships of various socio-demographic and attitudinal variables to respondents' intentions to use DRT for each of the four trip types. In the survey, DRT intentions were measured via an ordinal scale ranging from 1 ("Very Unlikely [to use DRT]") to 5 ("Very Likely [to use DRT]"). These results can most directly be analyzed using an ordered logit model, which is typically used when analyzing ordinal response variables. However, using ordered logit models would require that eight models be presented, one for each combination of trip purpose (commute / grocery / leisure / doctor) and service type (door-to-door / stop-to-stop). This would mean the impact and significance of socio-demographic / attitudinal factors would be varying across two axes (trip purpose and service type), which greatly increases the complexity of the analysis.

A determination was made to collapse the two ordered response variables for each trip purpose into a single binary variable for a clearer analysis. If a respondent answered "Likely" or "Very Likely" to either the door-to-door or the stop-to-stop offering for a given trip purpose, their response would be coded as a "yes" regarding intention to use DRT; otherwise, their response would be coded as a "no." This binary variable was used as the response variable in the first four logit models in section 4.2. The logit model was chosen because logit models are commonly used in transportation research to analyze the influences of individual factors on a binary modal choice outcome (Washington et al., 2020). After the first set of logit models, to check the robustness of the results, a second set of four logit models was developed based on the average of the two responses for each trip purpose. The response variable for these models was a binary measure of whether or not the average of the two DRT intention answers for each trip type (door-to-door & stop-to-stop) was greater than or equal to 3.5. So, for example, a respondent who answered "Not sure" (3) for door-to-door commuting DRT and "Likely" (4) for stop-to-stop commuting DRT would be marked as having positive DRT intentions for commuting. Results that repeat in both sets of models can be considered more robust than results that appear in only one of the two models.

To decide which predictor variables to include in the logit models, a univariate analysis of each socio-demographic and attitudinal covariate in the dataset was performed. Any variable that had

a p-value below .25 in a univariate logit model for either derived response variable was selected for inclusion in the preliminary model (the .25 cut-off is derived from Choudhary, 2006). After the preliminary model was specified, stepwise variable selection was performed using the "MASS" package in R to determine the covariates to include in the final model (Ripley et al., 2024).

Unlike the socio-demographic and attitudinal variables, individual levels of car dependency could not be measured directly with the survey. Therefore, a Latent Class Choice Model (LCCM) was used to separate respondents into different classes of car dependency. The LCCM combined subjective measures (the ease with which respondents believed they could perform the four types of trips without a car) with an objective measure (the distance to the nearest PT stop) to build a measure of car dependency that considered both individual and structural forces. The first step was to determine the ideal number of latent classes of car dependency to include in the analysis. In other words, how many distinct categories of car dependency should the respondents be sorted into? This decision was based on four factors: the AIC and BIC model fit indices, the number of observations in the smallest class, and general interpretability of the model. Lower AIC and BIC values indicate better model fit, while having a low number of observations in the smallest class means the model is less generalizable than a model with fewer, larger classes (Sinha et al., 2021). A model with only one class (representing a null hypothesis of no underlying heterogeneity) was included for comparison. Models were generated with the poLCA() function from the "poLCA" package in Rstudio (Linzer & Lewis, 2022).

After segmenting the sample into different car dependency classes, regression models were developed with the car dependency class as a predictor variable. In this case, because the analysis was focused on only a single variable of interest, the decision was made to present eight ordered logit models using the ordinal Likert scale responses collected for each trip type and service offering. To control for the effects of other individual characteristics, socio-demographic variables were also included in these models.

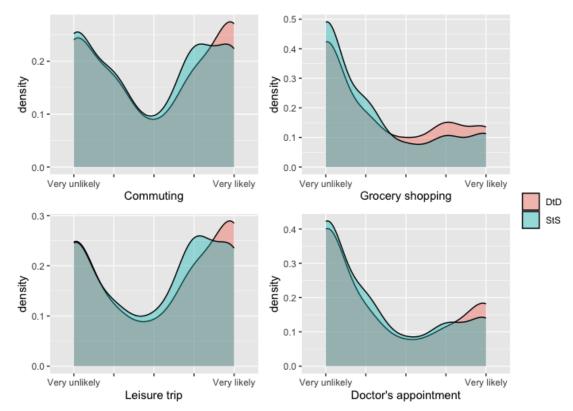
Multicollinearity was checked for among the predictor variables in each final model using the multiColLM() function from the "multiColl" package in R (Salmeron et al., 2022). First, a correlation matrix containing all variables was checked for any simple linear correlation above .70 (or below -.70), which would indicate collinearity. Assuming no such correlations were found, further measures to determine multicollinearity were checked following the procedure laid out by the package's authors (see Salmerón-Gómez et al., 2021).

4. Results

4.1 Impacts of Trip Characteristics

Figure 4 shows the distribution of Likert scale responses for each type of trip for both door-to-door (DtD) and stop-to-stop (StS) DRT options, giving a sense of the overall preferences of respondents for each of the four trip types. This figure also shows a direct comparison between the DtD and StS offerings at each level of likelihood to use. Commuting and leisure trips had higher rates of positive DRT intentions than negative DRT intentions, while the opposite is true for grocery shopping and doctor's appointment trips. In all four categories, DtD service overtook StS service at the upper end of the DRT intention scale.

Figure 4



Respondent Likelihood of Using DRT by Trip

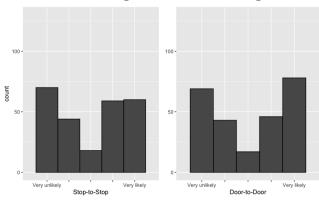
Note. Includes door-to-door (DtD) and stop-to-stop (StS) options.

Figure 5

100

count

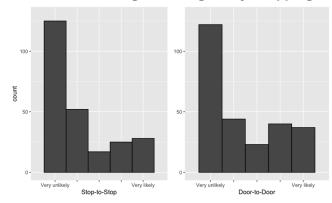
Histograms of DRT Intention Responses



Likelihood of using DRT for a leisure trip

100

Likelihood of using DRT for commuting



Likelihood of using DRT for grocery shopping



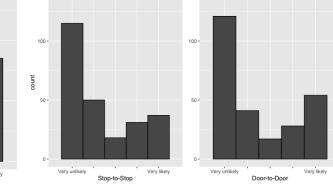
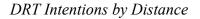


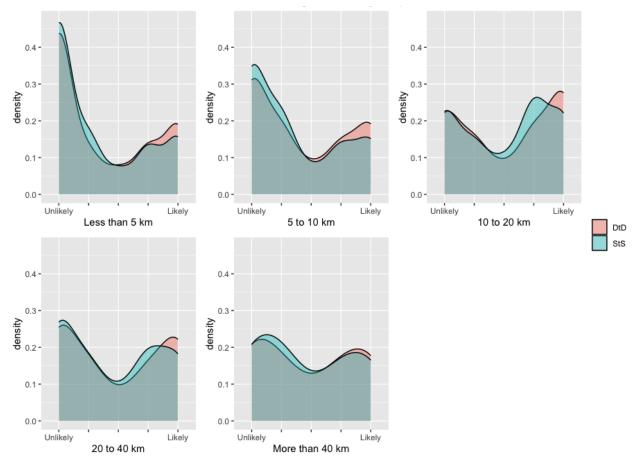
Figure 5 demonstrates these results in a histogram format, which give

Figure 5 demonstrates these results in a histogram format, which gives a better sense of the distribution of DRT intentions for each type of DRT service. Responses for commuting trips were about evenly split between likely and unlikely, with a slight skew towards likely for the door-to-door alternative. Responses for grocery trips and doctor's appointment trips skewed heavily towards unlikely. Responses for leisure trips skewed towards likely for both types of DRT service.

Figure 6 shows the impact of trip length on the intention to use DRT. This figure collapses all four types of trip together. The plots skew towards "unlikely" for trip distances below 10 km. Above that threshold, respondents were about equally likely and unlikely to use DRT. The 10 to 20 km range was the only range with more "likely" than "unlikely" responses. Again, door-to-door service consistently outperformed stop-to-stop service at the highest level of likelihood to use DRT.

Figure 6





Note. Includes door-to-door (DtD) and stop-to-stop (StS) options.

4.2 Impacts of Personal Characteristics and Attitudes

To measure the role of socio-demographic and social-psychological factors and in determining intentions to use DRT, logit models were developed for each of the four trip types presented in the survey. The response variable for these logit models was a binary variable measuring whether or not the respondent selected either "Likely" or "Very Likely" for at least one of the two DRT intention questions (i.e. door-to-door and/or stop-to-stop service). Predictor variables were determined via stepwise selection as described in section 3.4. Excluded variables were found to be insignificant in predicting model outcomes. Multicollinearity was not observed among the selected variables. The results of the logit models are presented in Table 3.

Table 3

	Comm			Commute					Leisur	·e			Doctor			
Variable	Esti- mate	Std. Error	p-value	Code	Esti- mate	Std. Error	p-value	Code	Esti- mate	Std. Error	p-value	Code	Esti- mate	Std. Error	p-value	Code
(Intercept)	-4.697	1.231	0.000	***	-3.244	1.252	0.010	**	-3.302	1.163	0.005	**	-3.517	1.259	0.005	**
Gender [†]	-0.555	0.306	0.070		0.435	0.329	0.185		-0.306	0.299	0.305		0.198	0.319	0.533	
Age over 45 years old	0.505	0.349	0.148		0.192	0.385	0.619		-0.226	0.343	0.509		-0.227	0.356	0.525	
Working for payment or profit	-0.162	0.313	0.604		-0.717	0.327	0.028	*	0.375	0.301	0.213		0.156	0.322	0.628	
Has young children (<6yrs.)	0.106	0.403	0.782		-0.941	0.463	0.042	*	-0.736	0.391	0.060	•	-1.200	0.454	0.008	**
Believes it would be easy to perform regular trips car-free	0.067	0.145	0.644		0.187	0.158	0.237		0.365	0.143	0.011	*	-0.130	0.153	0.398	
Satisfied with travel options	-0.190	0.110	0.085	•	-0.194	0.119	0.104		-0.182	0.106	0.086	•	-0.184	0.114	0.107	
Believes PT should be promoted to reduce traffic	0.270	0.187	0.149		0.054	0.206	0.794		0.146	0.183	0.426		0.307	0.204	0.132	
Believes environmental sustainability is important when choosing how to travel	-0.074	0.139	0.593		-0.084	0.155	0.589		-0.199	0.140	0.153		-0.324	0.146	0.026	*
Believes there should be more PT where they live	0.111	0.138	0.421		-0.024	0.146	0.868		0.201	0.135	0.137		0.054	0.151	0.720	
Tends to experiment with travel options before deciding	0.045	0.112	0.690		0.211	0.125	0.093		-0.020	0.109	0.857		0.111	0.118	0.346	
Comfortable using an app to request a DRT service	0.551	0.150	0.000	***	0.086	0.154	0.577		0.383	0.142	0.007	**	0.382	0.161	0.018	*
Believes robust DRT could replace the need for a car	0.483	0.114	0.000	***	0.717	0.125	0.000	***	0.331	0.108	0.002	**	0.521	0.117	0.000	***
Significance codes: 0 '***'	0.001	·**'	0.01 '*	° 0.05	·.' ().1 ''	1		•				•			

Logit Models for "Likely" or "Very Likely" Response to DRT Intentions with Individual-Level Characteristics

 $^{\dagger}0 =$ woman, 1 = man

Looking first at socio-demographic measures, gender and age were not found to be statistically significant predictors of DRT intentions for any of the four trip types. Working respondents were found to be less willing to use DRT for grocery shopping trips than non-working respondents, and respondents with young children at home were less willing to use DRT for grocery shopping trips or doctor's appointment trips.

For the attitudinal questions, believing it would be easy to perform regular trips without a car was associated with a greater intention to use DRT for leisure trips. On the other hand, having environmental motives when choosing how to travel made respondents less willing to use DRT for doctor's appointment trips. Only the attitudinal questions related to DRT were found to be consistent predictors of DRT intentions across trip types. Being comfortable with the thought of using a DRT app and believing DRT could serve as a car replacement were both associated with higher rates of DRT intentions for all trip types, with the exception of DRT app comfort not being a significant predictor for grocery trips. The variable measuring comfort sharing a DRT ride with strangers was excluded from the model during the initial univariate analysis, meaning it was not found to be a significant predictor of any DRT intention outcome.

To check the robustness of these results, a second set of logit models was generated with the same predictor variables. The response variable for these models is based on the average Likert scale response of the two DRT intention questions (door-to-door and stop-to-stop) for each trip type. If the average response was at least a 3.5, the respondent was marked as having positive DRT intentions for that trip type. The results of these models are presented in Table 4.

Table 4

Logit Models for Average Positive DRT Intentions with Individual-Level Characteristics

	Comm	nute			Groce	y			Leisur	·e			Doctor			
Variable	Esti- mate	Std. Error	p-value	Code	Esti- mate	Std. Error	p-value	Code	Esti- mate	Std. Error	p-value	Code	Esti- mate	Std. Error	p-value	Code
(Intercept)	-4.859	1.326	0.000	***	-4.620	1.433	0.001	**	-3.524	1.199	0.003	**	-2.953	1.296	0.022	*
Gender [†]	-0.467	0.312	0.133		0.233	0.357	0.513		-0.644	0.302	0.033	*	0.069	0.330	0.834	
Age over 45 years old	0.478	0.346	0.166		0.533	0.434	0.219		-0.030	0.342	0.928		-0.143	0.369	0.698	
Working for payment or profit	-0.147	0.316	0.640		-0.325	0.351	0.354		0.482	0.306	0.115		-0.062	0.335	0.851	
Has young children (<6yrs.)	-0.035	0.398	0.929		-1.459	0.569	0.010	*	-0.657	0.391	0.092	•	-1.044	0.470	0.026	*
Believes it would be easy to perform regular trips car-free	0.080	0.145	0.577		0.199	0.173	0.248		0.422	0.146	0.003	**	-0.012	0.159	0.936	
Satisfied with travel options	-0.107	0.109	0.329		-0.150	0.129	0.245		-0.216	0.107	0.043	*	-0.240	0.119	0.043	*
Believes PT should be promoted to reduce traffic	0.226	0.205	0.269		0.248	0.238	0.296		0.139	0.186	0.454		0.326	0.216	0.130	
Believes environmental sustainability is important when choosing how to travel	-0.057	0.141	0.685		-0.146	0.169	0.384		-0.239	0.141	0.091		-0.282	0.149	0.059	
Believes there should be more PT where they live	0.113	0.144	0.431		-0.110	0.161	0.491		0.161	0.137	0.240		-0.035	0.153	0.815	
Tends to experiment with travel options before deciding	0.005	0.111	0.962		0.260	0.138	0.06	•	0.014	0.110	0.892		0.052	0.121	0.663	
Comfortable using an app to request a DRT service	0.534	0.156	0.000	***	0.066	0.167	0.691		0.489	0.148	0.001	**	0.317	0.166	0.056	
Believes robust DRT could replace the need for a car	0.436	0.112	0.000	***	0.720	0.135	0.000	***	0.239	0.107	0.026	*	0.417	0.118	0.000	***
Significance codes: 0 '***'	0.001	·**)	0.01 '*'	° 0.05	; ·; ().1 ''	1						I			

 $^{\dagger}0 =$ woman, 1 = man

Only some of the results from the first set of logit models were reproduced in the second set. Once again, having young children at home negatively impacted DRT intentions for grocery shopping and doctor's appointment trips. Feeling it would already be easy to perform regular trips without a car was again associated with more positive DRT intentions for leisure trips. The positive impacts of the two DRT-related attitudinal measures on the four trip types were also reproduced, although the effects of feeling comfortable using a DRT app were not found to be significant for doctor's appointment trips. The negative relationship between working status and DRT intentions for grocery trips was not reproduced.

The average-based logit models also produced some significant results that were not found in the "Likely" / "Very Likely" logit models. For the socio-demographic measures, gender was found to be a significant predictor of DRT intentions for leisure trips, with women being more likely to use DRT for these trips than men. In terms of attitudes, satisfaction with current travel options had a negative impact on DRT intentions for both leisure trips and doctor's appointment trips.

Overall, the following associations among socio-demographic and attitudinal factors were found to be significant in in both models:

- Having young children at home is associated with less intention to use DRT for grocery trips and doctor's appointment trips.
- Feeling that it would currently be easy to perform regular trips without a car is associated with more intention to use DRT for leisure trips.
- Feeling comfortable using an app to request a DRT trip is associated with more intention to use DRT for commute and leisure trips.
- Believing that robust DRT could replace the need for a car entirely is associated with more intention to use DRT for all trip types.

The following associations among socio-demographic and attitudinal factors were found to be significant in only one of the two models:

- Being a woman is associated with more intention to use DRT for leisure trips.
- Working is associated with less intention to use DRT for grocery trips.
- Pro-environmental motives for travel behavior are associated with less intention to use DRT for doctor's appointment trips.
- Being satisfied with current travel options is associated with less intention to use DRT for leisure trips and doctor's appointment trips.
- Feeling comfortable using an app to request a DRT trip is associated with more intention to use DRT for doctor's appointment trips.

4.3 Car Dependency LCCM

A latent class choice model was developed to identify homogeneous sub-groups within the sample population on the basis of car dependency. The following variables were taken to be indicators of car dependency:

- nocarCommute/Leisure/Grocery/DoctorEase: the respondent's subjective interpretation of how easy it would be to perform various tasks without access to a personal vehicle.
- ptNear: a binary variable indicating whether or not the respondent has a public transit stop within a 15 minute walk of their home.

The results of the model specification process are shown in Table 5.

Table 5

Model 1		Mod	lel 2	Мос	lel 3	Model 4		
# of classes	1	# of classes	2	# of classes	3	# of classes	4	
AIC	2826	AIC	2642	AIC	2595	AIC	2583	
BIC	2883	BIC	2788	BIC	2829	BIC	2905	
Size of smallest class (#1)	219	Size of smallest class (#2)	105	Size of smallest class (#3)	59	Size of smallest class (#4)	34	

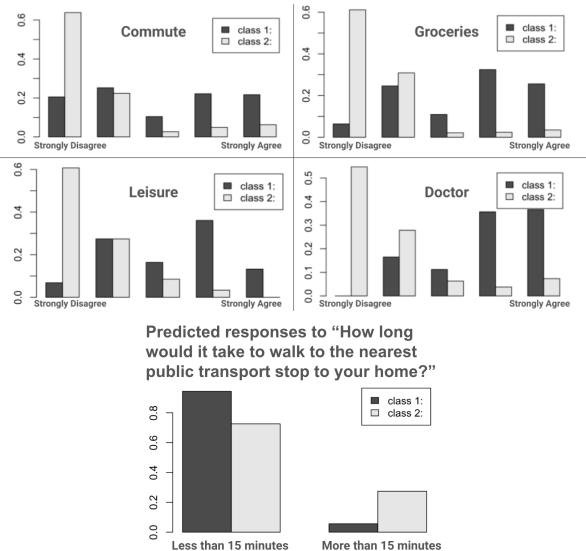
LCCM Specification Results

Model 2, with two latent classes, was selected. The AIC and BIC statistics of Model 2 were both better than those of Model 1, which assumed no underlying class distinction. Model 4 had a worse BIC statistic than the default model and was discarded. Although Model 3 had a better AIC statistic than Model 2, it also had a worse BIC statistic. Model 2 was selected for final analysis over Model 3 because a two-class model (high car dependency vs low car dependency) is easier to interpret than a three-class model, and because Model 2 had a larger smallest class than Model 3, meaning its results are more generalizable.

Figure 7 shows predicted responses for each class regarding how easy it would be to carry out regular tasks without a personal vehicle, as well as the predicted distance to the nearest public transit stop for each class. In the selected model, class 1 comprises respondents with mixed or low levels of car dependency, while class 2 comprises respondents with a high level of car dependency.

Figure 7

Predicted Responses for LCCM With Two Classes



Predicted responses to "It would be easy to do a _____ trip without a car"

Next, the car dependency class membership information derived from the LCCM was used to predict DRT intentions for the different trip types. Ordered logit models were generated for each trip type including class membership as well as other social demographic controls. Multicollinearity was not observed among the covariates of the models. The results of these models are presented in Table 6.

Table 6

				Com	nuting					
		Door-to	o-Door		Stop-to-Stop					
Variable	Coefficient	Std. Error	p-value	Significance	Coefficient	Std. Error	p-value	Significance		
Class†	-0.04346	0.26357	0.869		-0.095718	0.25706	0.710			
Over 45	0.14907	0.27782	0.592		0.284075	0.27362	0.299			
Gender ^{††}	-0.64756	0.26381	0.014	*	-0.475264	0.26439	0.072			
Has young children (<6yrs.)	-0.02954	0.34016	0.931		0.021547	0.34321	0.950			
>75k yr. income	0.27396	0.25500	0.283		0.144198	0.25112	0.566			
1 2	-0.98716	0.46747	0.035	*	-0.954894	0.46023	0.038	*		
2 3	-0.23743	0.46297	0.608		-0.188700	0.45583	0.679			
3 4	0.03276	0.46366	0.944		0.082946	0.45512	0.855			
4 5	0.75675	0.46798	0.106		1.176595	0.46175	0.011	*		

Ordered Logit Models for DRT Intentions with Latent Class Variable

				Leisu	re Trip						
		Door-to	o-Door		Stop-to-Stop						
Variable	Coefficient	Std. Error	p-value	Significance	Coefficient	Std. Error	p-value	Significance			
Class [†]	-0.53817	0.25890	0.038	*	-0.505715	0.26199	0.054	•			
Over 45	-0.23605	0.27555	0.392		-0.339128	0.28120	0.228				
Gender ^{††}	-0.44472	0.26049	0.088		-0.597885	0.26403	0.024	*			
Has young children (<6yrs.)	-0.12575	0.33670	0.709		0.039336	0.34741	0.910				
>75k yr. income	0.25011	0.25223	0.321		0.113723	0.25544	0.656				
1 2	-1.96508	0.47568	0.000	***	-2.134302	0.48395	0.000	***			
2 3	-1.47770	0.46573	0.002	**	-1.580703	0.47378	0.001	**			
3 4	-1.15153	0.45914	0.012	*	-1.210241	0.46787	0.010	*			
4 5	-0.23334	0.45185	0.606		0.054167	0.45991	0.906				

				Grocery	Shopping					
		Door-to	o-Door		Stop-to-Stop					
Variable	Coefficient	Std. Error	p-value	Significance	Coefficient	Std. Error	p-value	Significance		
Class [†]	-0.11350	0.26240	0.665		-0.16709	0.27867	0.710			
Over 45	-0.00499	0.28295	0.986		0.35388	0.29404	0.299			
Gender ^{††}	0.07302	0.26618	0.784		-0.10397	0.27705	0.072			
Has young children (<6yrs.)	-0.43853	0.34790	0.207		-0.28320	0.36739	0.950			
>75k yr. income	-0.02769	0.25355	0.913		-0.31323	0.26810	0.566			
1 2	-0.40318	0.46263	0.383		-0.22456	0.48336	0.038	*		
2 3	0.29594	0.46227	0.522		0.72277	0.48458	0.679			
3 4	0.67506	0.46501	0.147		1.07306	0.48831	0.855			
4 5	1.65635	0.48308	0.001	**	1.90445	0.50958	0.011	*		

Doctor's Appointment												
	Door-to	o-Door		Stop-to-Stop								
Coefficient	Std. Error	p-value	Significance	Coefficient	Std. Error	p-value	Significance					
-0.08332	0.26405	0.752		-0.10227	0.26905	0.704						
-0.19198	0.28674	0.503		-0.27139	0.28955	0.349						
-0.28874	0.26984	0.285		-0.57788	0.27594	0.036	*					
-0.80663	0.36339	0.026	*	-0.86969	0.36676	0.018	*					
0.10269	0.25859	0.691		0.10969	0.26191	0.675						
-0.62304	0.48124	0.195		-0.85583	0.48634	0.078						
0.07947	0.47943	0.868		0.04557	0.48399	0.925						
0.33118	0.47999	0.490		0.39001	0.48686	0.423						
0.94671	0.48544	0.051		1.13068	0.49769	0.023	*					
	-0.08332 -0.19198 -0.28874 -0.80663 0.10269 -0.62304 0.07947 0.33118	Coefficient Std. Error -0.08332 0.26405 -0.19198 0.28674 -0.28874 0.26984 -0.80663 0.36339 0.10269 0.25859 -0.62304 0.48124 0.07947 0.47943 0.33118 0.47999	-0.08332 0.26405 0.752 -0.19198 0.28674 0.503 -0.28874 0.26984 0.285 -0.80663 0.36339 0.026 0.10269 0.25859 0.691 -0.62304 0.48124 0.195 0.07947 0.47943 0.868 0.33118 0.47999 0.490	Door-to-Door Coefficient Std. Error p-value Significance -0.08332 0.26405 0.752 -0.19198 0.28674 0.503 -0.28874 0.26984 0.285 -0.28874 0.26984 0.285 * -0.28874 0.26984 0.285 * -0.10269 0.36339 0.026 * -0.10269 0.25859 0.691 * -0.62304 0.48124 0.195 -0.07947 0.47943 0.868 <	Door-to-Door Significance Coefficient Std. Error p-value Significance Coefficient -0.08332 0.26405 0.752 -0.10227 -0.19198 0.28674 0.503 -0.27139 -0.28874 0.26984 0.285 -0.57788 -0.80663 0.36339 0.026 * -0.86969 0.10269 0.25859 0.691 * -0.85583 -0.62304 0.48124 0.195 -0.85583 0.04557 0.33118 0.47999 0.490 0.490 0.39001	Door-to-Door Stop-to Coefficient Std. Error p-value Significance Coefficient Std. Error -0.08332 0.26405 0.752 -0.10227 0.26905 -0.19198 0.28674 0.503 -0.27139 0.28955 -0.28874 0.26984 0.285 -0.57788 0.27594 -0.80663 0.36339 0.026 * -0.86969 0.36676 0.10269 0.25859 0.691 * 0.10969 0.26191 -0.62304 0.48124 0.195 -0.85583 0.48634 0.07947 0.47943 0.868 0.04557 0.48399 0.33118 0.47999 0.490 0.39001 0.48686	Door-to-Door Stop-to-Stop Coefficient Std. Error p-value Significance Coefficient Std. Error p-value -0.08332 0.26405 0.752 -0.10227 0.26905 0.704 -0.19198 0.28674 0.503 -0.27139 0.28955 0.349 -0.28874 0.26984 0.285 -0.57788 0.27594 0.036 -0.80663 0.36339 0.026 * -0.86969 0.36676 0.018 0.10269 0.25859 0.691 - - -0.85583 0.48634 0.078 -0.62304 0.48124 0.195 -0.85583 0.48634 0.078 0.07947 0.47943 0.868 0.423 0.39001 0.48686 0.423					

[†] 1 = low / mixed car dependency, 2 = high car dependency ^{††} 0 = woman, 1 = man

Compared to being in the low-to-mid car dependence class, membership in the high car dependence class was significantly (p < .05) associated with less intention to use a door-to-door DRT service for a leisure trip. The sign of the class coefficient was negative for all other DRT intention models as well, although only for the stop-to-stop leisure trip model did this relationship approach statistical significance (p=.054).

5. Discussion

The results of the survey demonstrate that drivers in the commuter belt have strong beliefs about how they would and would not use a DRT service. A few patterns emerged across different trip types and demographic groups. In general, respondents were more likely to select responses at either extreme of the scale than they were to select responses in the middle, indicating that most respondents had a strong sense that they either did or did not intend to use DRT. The responses also showed a widespread preference for door-to-door service; across all trip distances and all trip types, door-to-door DRT received more "Very Likely" responses than stop-to-stop DRT.

Surprisingly, nearly two-thirds of survey respondents were women. One possible explanation would be that women were more likely to be home between the hours of 9am and 5pm, when the mailslot surveys were delivered. Census data shows that women in Ireland have a lower rate of employment than men (Central Statistics Office, 2023). However, 75% of women respondents in the current study reported their principal status as "working for payment or profit," compared to 70% of men, so this explanation is insufficient to explain the observed gender discrepancy. Alternatively, it is possible that women were more active on the social media groups by which the survey was also distributed, and/or that women were more inclined to respond to the survey invitation than men. The potential impacts of this sampling bias will be discussed in section 6.2.

Trip-level variables played a significant role in determining DRT intentions. Only two of the four trip types had a larger proportion of respondents willing to use DRT than not: commuting and leisure trips. These two categories have generally been assumed to be the primary travel purposes of DRT users (Schasché et al., 2022), however, this finding does push back against previous findings that drivers would be less willing to use DRT for leisure trips than for commuting (Saxena et al., 2020). Doctor visits fared very poorly in the survey. Previous studies have examined hospital access as a potential niche DRT application (Ryley et al., 2014), but based on the results of the present study, car users showed little intention of using DRT for medical trips. Medical facilities in the study area are already fairly well-served by traditional PT, which may decrease the desirability for DRT service. Grocery trips also fared poorly. It is likely that DRT has a difficult time making up for the advantages offered by personal vehicles for grocery shopping, e.g. easier loading/unloading of items and more personal storage space. In terms of trip distance, respondents were generally uninterested in using DRT for trips under 10

km, and above 20 km results were mixed but leaned towards rejecting DRT. The amount of variation in DRT uptake across different trip distances highlights the importance of analyzing trip-level characteristics for understanding the intentions of potential DRT users.

In terms of individual-level determinants of DRT intentions, socio-demographic factors were generally found to be less impactful than attitudinal factors. Education, income level, and age were not found to be significant predictors of DRT intentions for any of the four trip types in the logit models. Gender was a significant predictor in only one case: women were more likely to use DRT for leisure trips than men according to the "average" logit model (Table 4). This does raise interesting questions regarding the intersection of trip purpose and gender in determining DRT intentions. For example, this finding could derive from differences in the particular type of leisure trip reported by male versus female respondents. However, given that the finding was not reproduced with statistical significance in the other logit model, it should be interpreted with caution. Further research is needed to determine if there is a difference in how gender impacts intentions to use DRT (or other forms of shared transit) based on expected trip purpose. Similarly, the only significant finding regarding principal status was that working people were less likely to use DRT for grocery shopping than non-workers, but this result was produced in only one of the two grocery shopping logit models.

The lack of significant findings for most of these socio-demographic categories stands in contrast to the bulk of previous DRT literature, which has usually found significant (but conflicting) relationships to DRT use for gender, income, education, age, and principal status (Schasché et al., 2022). Given the preponderance of previous evidence showing the import of these socio-demographic categories in DRT uptake, it is possible that these factors are, in fact, predictive of DRT intentions in the study area, but that their impact was too low to be measured with significance given the current study's methodology and sample size. Regardless, it is worth pointing out that social-psychological variables generally had more of an impact on DRT intentions in the second variables generally had more of an impact on DRT intentions in the second variables generally had more of an impact on DRT intentions in the second variables generally had more of an impact on DRT intentions in the second variables generally had more of an impact on DRT intentions in the second variables generally had more of an impact on DRT intentions in the second variables generally had more of an impact on DRT intentions in the second variables generally had more of an impact on DRT intentions in the present study than these socio-demographic variables.

The one socio-demographic variable found to consistently affect DRT intentions for multiple trip types was the presence of young children in the household. Both models found this variable to significantly decrease the likelihood of a respondent using DRT for grocery shopping trips and doctor's appointments trips. Previous research has found that the presence of young children in a household is positively associated with that household being car-oriented, likely because cars are seen as particularly well-suited to meeting the travel needs of children (Lu et al., 2022). However, the impact of having young children on DRT intentions specifically has not previously been studied. The present findings indicate that having young children in one's household has a similar effect on one's DRT use as it does for other forms of shared transportation.

Social-psychological factors played a more consistent role in influencing DRT intentions than socio-demographic factors. Key among these was perceived behavioral control. Respondents who felt that they would easily be able to use an app to request a DRT ride were significantly more likely to use DRT for commuting and leisure trips — a finding that was replicated in both sets of logit models. Given that app-based DRT is still an emergent and uncommon form of travel, it is unsurprising that perceptions of how easy it would be to use the travel mode are key predictors of intention. In addition, a general belief that it would be easy to perform regular trips car-free was significantly positively associated with DRT intentions for leisure trips in both models. This may indicate an increased sensitivity to perceived behavioral control for specifically leisure trips. Because these trips are ostensibly less necessary than commuting, grocery, or doctor's trips, the ease with which these trips can be done by DRT may play a more important role in determining intention than for other trip types.

Attitudes, both towards DRT and towards travel in general, were also important predictors of DRT intentions. As predicted, attitudes towards sharing rides did not have a significant impact on DRT uptake. On the other hand, respondents who believed DRT could replace the need for cars entirely were consistently more likely to use DRT across all four trip types. Given that DRT attitudes influence DRT desires, and DRT desires influence DRT intentions, this finding is not surprising. What is surprising is the finding that pro-environmental attitudes reduced DRT intentions for doctor's appointments. In the "Likely" / "Very Likely" logit model (Table 3), respondents who believed that environmental sustainability is an important consideration when selecting travel mode were less likely to select DRT for doctor's appointments. This result was not reproduced as significant in the "average" logit model, so it is possible that this finding is spurious and not representative of the population as a whole. Still, this finding is unexpected given the positive association between pro-environmental motives and use of other forms of shared transportation (Bouscasse et al., 2018). More research should be conducted into understanding the impact of environmental motives on DRT intentions, as this remains understudied compared to other travel modes.

The results of the LCCM and the subsequent ordered logit models incorporating car dependency indicate that DRT intentions are generally not strongly constrained by car dependency. However, intentions for the door-to-door leisure trip DRT offering did decrease when drivers belonged to the higher car dependency class. This finding likely derives from the fact that the existing transportation landscape of the study area as described in section 3.1 provides more constraints on leisure trips than other trip types. This is because the existing PT is largely oriented towards commuters and runs most frequently during commuting hours, while leisure trips happen mostly outside of those hours. This also entrenches the habit of car usage for leisure trips in highly car-dependent drivers, therefore reducing intentions to switch away from car usage for these trips.

6. Conclusion

Trip characteristics and traveler characteristics both play an important role in influencing DRT intentions. For trips, in the context of Dublin's commuter belt, commuting and leisure trips in the range of 10–40 km correspond to the highest rates of DRT intent among drivers. For travelers, social-psychological factors have a stronger impact than socio-demographic factors in influencing DRT intentions. Perceived behavioral control is an especially important contributor to DRT uptake: the more drivers believe it would be easy to use a DRT service, the more willing they are to use it. Experiencing a high level of car dependence does not seem to pose a significant constraint on DRT intentions for most trip types, with the exception of leisure trips, where intention to use door-to-door service suffers among highly car dependent respondents to a statistically significant degree. Understanding why travelers choose a given mode of travel requires understanding how built environment, traveler-level, and trip-level variables influence a given mode's desirability to potential users. In particular, this thesis highlights the importance of social-psychological factors in determining mode choice intentions, which have hereto been largely ignored in research on DRT. Greater knowledge of the variables underpinning mode choice in the case of DRT will allow operators to develop more robust and sustainable systems that can serve as a viable car alternative in car-dependent regions.

6.1 Policy Recommendations

The results of the present study demonstrate that a DRT system in Dublin's commuter belt should aim to operate at an inter-town scale, rather than serving primarily intra-town trips. Because survey responses indicated a preference for DRT trips above 10 km in distance, the minimum coverage area of a successful DRT system would need to be large enough to at least include a few neighboring municipalities. "City hopper" DRT systems have seen success in similar regions in the past. One example is the kvgOF Hopper system in Germany. The system opened in 2022 and serves the Offenbach district (pop. ~360,000), which includes many of the southern suburbs of Frankfurt (Schürrlein, 2022). Given the similar spatial context, such a service would likely be feasible to run in the Greater Dublin Area as well.

A classic pitfall of failed DRT systems is that they try to offer too flexible of a service in too large of an area all at once. Successful DRT systems often grow incrementally, starting with routes that serve specific, acute transportation needs before expanding into more general operations (Enoch et al., 2006). The results of the present study indicate two possible niches that a DRT system in the Greater Dublin Area could focus on as it begins operations. The first is a commuting niche targeting commutes in the 10–40 km range, especially commutes between commuter towns. As it stands, commuters going to or from Dublin are fairly well-served by bus and train services. However, commuters traveling between commuter towns have relatively fewer non-car options. A DRT service offering transport between commuter towns on a semi-fixed daily schedule at peak commuting times could attract a lot of daily users. Such a

service would greatly increase the amount of trips in this area for which viable non-car options exist.

Travel time reliability has been found to be a more important factor for commuting trips than for most other trips (G. Zhang et al., 2024). Unfortunately, this is at odds with survey respondents' preference for door-to-door service over stop-to-stop service for commuting trips. Door-to-door services tend to have much greater variability in departure time and travel time, as routes can be significantly lengthened by diversions away from main roads to pick up or drop off passengers. Historically, this problem has been exacerbated in areas with circuitous road networks and many cul-de-sacs (Enoch et al., 2006). Reliability was not included in the comparison between door-to-door and stop-to-stop service presented to survey respondents. While respondents were willing to pay more and take longer trips for door-to-door commuting service, in reality a stop-to-stop service could be operated would be with set departure and arrival times for each town, but with flexibility in which stops are serviced at each town. This would give commuters a reliable benchmark for when they will arrive at their destination while still allowing them to benefit from the pick-up and drop-off location flexibility offered by a DRT service.

Leisure trips offer another possible niche for DRT operators in the commuter belt. Unlike a commuter-focused service, a leisure-focused DRT service could benefit from trading off some travel time reliability for greater flexibility. A leisure-oriented system would operate door-to-door service primarily in the evenings and on weekends, although some weekday service could be implemented for retired customers and people working irregular hours. The system could place major vehicle hubs at popular leisure destinations, such as cinemas or shopping centers.

One downside of the leisure trip approach is that, based on the analysis of the impact of car dependence on DRT intentions, highly car-dependent people would be less likely to use DRT for leisure trips than less car-dependent people. As a result, the impact of a leisure-oriented DRT system on car dependency would be less pronounced than a commute-oriented system. However, the social benefits of a leisure-oriented DRT system extend beyond offering an alternative for car users. Because public transit in the Greater Dublin Area is already oriented towards commuters, people facing car deprivation have significantly fewer options for leisure trips than their car-owning counterparts. This perpetuates social exclusion in a group that is already largely composed of socially and economically marginalized people (Mattioli & Colleoni, 2016). Increasing the transit accessibility of popular leisure destinations would alleviate some of the social exclusion caused by car deprivation in car-dependent areas.

6.2 Limitations

Stated preference techniques have well-documented limitations when applied to transportation research. In short, there is a difference between what people say they will do and what people actually do (Train, 2002). Respondents may bias their responses by trying to appear more socially respectable, for example, or by trying to answer in the way they assume the researcher "wants" them to respond. Additionally, when conducting an SP survey for a travel mode that does not yet exist, there may be significant differences between how respondents imagine the travel mode to be and how it would actually function. Several steps were taken to minimize the impacts of these SP limitations. For example, the respondent's current mode of transportation was used as the baseline against which to compare DRT alternatives, which made the decision situations more realistic by mimicking the actual travel options people would have if a robust DRT system existed (Carroll et al., 2017). Additionally, each type of trip was separated into its own section to minimize task complexity, which has been shown to correlate with anomalies in SP surveys (Carlsson, 2010). Ultimately, however, it is important to keep in mind that the findings in this study are based on how people believe they would behave rather than observed behavior.

The overrepresentation of women and underrepresentation of men in the sample introduces sampling bias into the results. If women differed significantly from men in their responses to the DRT intention questions, then that difference would have had an outsized impact on the final DRT intention results compared to a population-wide census. According to the logit models used in section 4.2, women were more likely to display DRT intentions for commuting and leisure trips than men, while the opposite was true for grocery shopping and doctor's appointment trips. So, it is possible that the results discussed in section 4.1 for commuting and leisure trips are biased in favor of positive DRT intentions, and results for grocery and doctor trips biased in favor of negative DRT intentions, compared to the population of interest. However, the impact of gender on DRT intentions was not found to be statistically significant in seven of the eight logit models presented in 4.2, so the impact of the over-representation of women on these findings is somewhat tempered. Still, the bias introduced by this sample should be considered when interpreting the results of this study.

Other research limitations were introduced due to time and budgetary restraints. Because survey invitations were dropped off to random households and no incentives were offered for participation, there may be a strong response bias towards people who feel strongly about the subject of transportation and/or have the free time to respond to a survey without compensation. The survey was also distributed on social media, which can diminish the quality of survey responses and bias the sample towards people with internet access and a social media presence (Ong et al., 2023). Certain demographic categories were able to be compared with known census data, but other personal characteristics in the sample population (such as interest in public transit) may have varied significantly from the study area.

Additional research limitations were introduced through the emphasis on anonymity in the survey design. Personal data was not collected from respondents for privacy reasons and to minimize data handling risks. However, having access to data such as respondents' home, work, and leisure locations would allow for a more precise investigation of the spatial factors influencing DRT intentions. Being able to recruit a panel of respondents for a confidential survey, rather than an anonymous survey, would have allowed for the collection of higher-quality data (Murdoch et al., 2014). Additionally, allowing respondents to skip questions at-will meant that many respondents did not return a full set of answers. This necessitated the use of imputation, which may have dampened the significance of otherwise impactful individual-level variables in the final regression models.

6.3 Directions for Future Research

The specific impacts of attitudes, desires, and subjective norms on DRT intentions deserves further consideration. In particular, this study found some surprising results regarding the role of environmental motives in predicting DRT intentions. Further studies could combine such questions about environmental attitudes with additional questions assessing the affective dimension of car and DRT usage. In other words, regardless of how people *intend* to travel, do people *want* to use cars and/or DRT for travel? This analysis could both strengthen our understanding of the connection between pro-environmental attitudes and DRT intentions as well as untangle the impact of travel mode desire from the impact of travel attitudes.

Future research could also test the generalizability of the results found in the current case study, as well as those derived from previous stated preference DRT surveys, by utilizing a multiple-case research design that examines several geographic sites. For example, researchers could select multiple peri-urban sites around the world with high levels of car dependency, and see whether significant differences arise in the viability of DRT based on various social and/or spatial factors. This research would help to identify the extent to which determinants of DRT intention are consistent across multiple peri-urban contexts.

As far as the current case study is concerned, if a DRT program was actually piloted in the study area, revealed preference techniques could be used to better understand how personal and trip characteristics impact DRT intentions. A pilot DRT program would also allow researchers to perform natural experiments comparing travel behavior before and after the introduction of a new transport option to test for a modal shift away from cars.

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Appendix A: Survey

Thank you for opening this survey about transportation in the Greater Dublin Area! Your interest is greatly appreciated.

Please answer the following questions to determine your eligibility for this survey.

Do you own or have access to a car / van / motorcycle for day-to-day use?

o Yes (1)

o No (2)

Are you 18 years or older?

o Yes (1)

o No (2)

Please select the option which best describes where you live:

o Dublin city center (within the canals) (1)

o Inner suburbs of Dublin (within the M50 motorway) (2)

o Outer suburbs of Dublin (outside the M50 motorway) (3)

o Commuter town outside Dublin (4)

o Elsewhere in Co. Dublin, Louth, Meath, Kildare, or Wicklow (5)

o None of the above (6)

Screened Out

Unfortunately, you do not meet the eligibility requirements for this survey. Thank you for your time.

Informed Consent

You are warmly invited to participate in a research project about Demand-Responsive Transportation (DRT) in the Greater Dublin Area. This online survey should take about 10 to 15 minutes to complete. You will be asked about your travel behaviour and attitudes towards various forms of transportation, as well as some relevant demographic information. Participation is voluntary, and responses will be kept anonymous. You have the option to not respond to any questions that you choose.

This research is being undertaken as part of a master's thesis project at Utrecht University, with collaboration from Trinity College Dublin. We may use or share your research information for future research studies. This research may be similar to this study or different. We will not ask for your additional informed consent for these studies.

If you have any questions about the research, please contact Paul Molamphy, the principal researcher, via email at p.m.molamphy@students.uu.nl or the faculty advisor, Dr. Dick Ettema, at d.f.ettema@uu.nl.

Please use the below selection to indicate your consent to participate in this research:

I consent to participate in this research project and affirm that I am at least 18 years of age.

o Yes (1)

o No (2)

Current transport

Section 1 (of 4)

This section focuses on your current transportation situation.

How many cars are owned or are available for use by one or more members of your household?

o 0 cars (1) o 1 car (2) o 2 cars (3) o 3 cars (4) o 4 or more cars (5)

Do you have a driving license?

o Yes (1)

o No (2)

How many people living in your household (including yourself) have a driving license?

o 0 people (1)

o 1 person (2)

o 2 people (3)

o 3 people (4)

o 4 or more people (5)

Is free parking available at your workplace or place of education?

o Yes (1)

o No (2)

o N/A or not sure (3)

On average, how often do you use public transportation?

o Once a month or less (1)

o Multiple times per month (2)

o About once a week (3)

o Multiple times per week (4)

o Daily (5)

How long would it take to walk to the nearest public transport stop to your home? (Bus, train, DART, or LUAS)

- o Less than 5 minutes (1)
- o 5-10 minutes (2)
- o 10–15 minutes (3)
- o 15-30 minutes (4)
- o More than 30 minutes (5)
- o I do not know of any public transport stops near my home (6)

How difficult do you think it would be for you to do the following things without access to a car?

	Very difficult (1)	Moderately difficult (2)	Neither easy nor difficult (3)	Moderately easy (4)	Very easy (5)	Don't know or N/A (6)
Travel to work or school (1)	0	0	0	0	0	0
Go grocery shopping (2)	0	0	0	0	0	0
Do my favorite leisure activity outside my neighborhood (for example, going out to eat, going to the cinema, or seeing a concert / theatre performance) (4)	0	0	0	0	0	0

Go to a doctor's appointment (5)	0	0	0	0	0	0

DRT Scenarios

Section 2 (of 4)

This section will ask about your willingness to use demand-responsive transportation for four different trips.

Demand-responsive transportation, or **DRT**, refers to a public transit system that operates like a mix between an **individual taxi** and a **traditional bus**. In this system, you would request a ride by phone or through an app and a minibus would pick you up to take you to your destination. Along the way, the driver would follow a route that allows them to **pick up and drop off other passengers as well.**

Overall, this system would be less expensive than a regular taxi and more flexible than a regular bus service, but trips would take longer than they would by car or by a regular taxi.

A DRT system can be **door-to-door**, meaning the minibus picks you up from your home and drops you off right at your destination, or **stop-to-stop**, meaning the minibus picks you up at a designated stop near your starting point (such as a school, a church, or a grocery store) and drops you off at the closest stop to your destination.

For the sake of this survey, imagine you had access to a DRT system with the following fares and travel times (exact numbers will be calculated for you on the following pages):

Trip 1: Commute

If you do not currently attend work or school, please answer the following questions based on your most recent typical trip to work or school.

How do you usually travel to work or school?

o On foot (1)

o Bicycle (2)

o Bus, minibus, or coach (3)

o Train, DART, or LUAS (4)

o Car / van / motorcycle (as driver) (5)

o Car / van / motorcycle (as passenger) (6)

o Other (7) _____

o N/A / I don't travel for this (8)

About what distance is your work or school commute? (One-way)

o Less than 5 km (1)

o 5-10 km (2) o 10-20 km (3) o 20-40 km (4) o More than 40 km (6) o N/A / I don't travel for this (7)

Trip 1: Commute

For a <5km trip:

- A door-to-door DRT trip would likely cost €2.20 and take less than 15 minutes.

- A stop-to-stop DRT trip would likely cost €2.00 and take less than 20 minutes, including walk time to and from stations.

For a 5-10km trip:

- A door-to-door DRT trip would likely cost about €4 and take about 15–20 minutes.

- A **stop-to-stop** DRT trip would likely cost about €3.50 and take about 20–25 minutes, including walk time to and from stations.

For a 10-20km trip:

- A door-to-door DRT trip would likely cost about €5 and take about 25–30 minutes.

- A **stop-to-stop** DRT trip would likely cost about €4.50 and take about 25–30 minutes, including walk time to and from stations.

For a 20-40km trip:

- A door-to-door DRT trip would likely cost about €10 and take about 35–55 minutes.

- A **stop-to-stop** DRT trip would likely cost about €8 and take about 30–45 minutes, including walk time to and from stations.

For a 40+km trip:

- A door-to-door DRT trip would likely cost more than €12 and take longer than 55 minutes.

- A stop-to-stop DRT trip would likely cost more than €10 and take longer than 45 minutes, including walk time to and from stations.

How likely would you be to use the following DRT options for this trip, if they were available to you?

	Very unlikely (1)	Moderately unlikely (2)	Neither likely nor unlikely (3)	Moderately likely (4)	Very likely (5)	Not sure / I don't make this trip (6)
Door-to-Do or (1)	0	0	0	0	0	0
Stop-to-Sto p (2)	0	0	0	0	0	0

Trip 2: Grocery Shopping

How do you usually travel to get groceries?

o On foot (1)

o Bicycle (2)

o Bus, minibus, or coach (3)

o Train, DART, or LUAS (4)

o Car / van / motorcycle (as driver) (5)

o Car / van / motorcycle (as passenger) (6)

o Other (7) _____

o N/A / I don't travel for this (8)

About what distance is your average grocery shopping trip? (One-way)

o Less than 5 km (1)

o 5-10 km (2)

o 10-20 km (3)

o 20-40 km (4)

o More than 40 km (6)

o N/A / I don't travel for this (7)

Trip 2: Grocery Shopping

For a <5km trip:

- A door-to-door DRT trip would likely cost €2.20 and take less than 15 minutes.

- A stop-to-stop DRT trip would likely cost €2.00 and take less than 20 minutes, including walk time to and from stations.

For a 5-10km trip:

- A door-to-door DRT trip would likely cost €4 and take about 15–20 minutes.

- A **stop-to-stop** DRT trip would likely cost €3.50 and take about 20–25 minutes, including walk time to and from stations.

For a 10-20km trip:

- A door-to-door DRT trip would likely cost about €5 and take about 25–30 minutes.

- A **stop-to-stop** DRT trip would likely cost about €4.50 and take about 25–30 minutes, including walk time to and from stations.

For a 20-40km trip:

- A door-to-door DRT trip would likely cost about €10 and take about 35–55 minutes.

- A **stop-to-stop** DRT trip would likely cost about €8 and take about 30–45 minutes, including walk time to and from stations.

For a 40+km trip:

- A door-to-door DRT trip would likely cost more than €12 and take longer than 55 minutes.

- A stop-to-stop DRT trip would likely cost more than €10 and take longer than 45 minutes, including walk time to and from stations.

How likely would you be to use the following DRT options for this trip, if they were available to you?

	Very unlikely (1)	Moderately unlikely (2)	Neither likely nor unlikely (3)	Moderately likely (4)	Very likely (5)	Not sure / I don't make this trip (6)
Door-to-Do or (1)	0	0	0	0	0	0
Stop-to-Sto p (2)	0	0	0	0	0	0

Trip 3: Leisure

For the following section, think of a leisure activity that you enjoy doing outside of your neighborhood (such as going out to eat, going to the cinema, going to a concert, or going to see a theatre performance)

How do you usually travel to get to your chosen leisure activity?

```
o On foot (1)
```

```
o Bicycle (2)
```

o Bus, minibus, or coach (3)

o Train, DART, or LUAS (4)

o Car / van / motorcycle (as driver) (5)

o Car / van / motorcycle (as passenger) (6)

o Other (7)_____

o N/A / I don't travel for this (8)

About what distance is your average trip to the leisure activity? (One-way)

```
o Less than 5 km (1)
```

o 5-10 km (2)

o 10-20 km (3)

o 20-40 km (4)

o More than 40 km (6)

o N/A / I don't travel for this (7)

Trip 3: Leisure

For a <5km trip:

- A door-to-door DRT trip would likely cost €2.20 and take less than 15 minutes.

- A stop-to-stop DRT trip would likely cost €2.00 and take less than 20 minutes, including walk time to and from stations.

For a 5-10km trip:

- A door-to-door DRT trip would likely cost €4 and take about 15–20 minutes.

- A **stop-to-stop** DRT trip would likely cost €3.50 and take about 20–25 minutes, including walk time to and from stations.

For a 10-20km trip:

- A door-to-door DRT trip would likely cost about €5 and take about 25–30 minutes.

- A **stop-to-stop** DRT trip would likely cost about €4.50 and take about 25–30 minutes, including walk time to and from stations.

For a 20-40km trip:

- A door-to-door DRT trip would likely cost about €10 and take about 35–55 minutes.

- A **stop-to-stop** DRT trip would likely cost about €8 and take about 30–45 minutes, including walk time to and from stations.

For a 40+km trip:

- A door-to-door DRT trip would likely cost more than €12 and take longer than 55 minutes.

- A stop-to-stop DRT trip would likely cost more than €10 and take longer than 45 minutes, including walk time to and from stations.

	Very unlikely (1)	Moderately unlikely (2)	Neither likely nor unlikely (3)	Moderately likely (4)	Very likely (5)	Not sure / I don't make this trip (6)
Door-to-Do or (1)	0	0	0	0	0	0
Stop-to-Sto p (2)	0	0	0	0	0	0

How likely would you be to use the following DRT options for this trip, if they were available to you?

Trip 4: Go to a doctor's appointment

How do you usually travel to go to doctor's appointments?

o On foot (1)

o Bicycle (2)

o Bus, minibus, or coach (3)

o Train, DART, or LUAS (4)

o Car / van / motorcycle (as driver) (5)

o Car / van / motorcycle (as passenger) (6)

o Other (7) _____

o N/A / I don't travel for this (8)

About what distance is your average trip to visit the doctor? (One-way)

o Less than 5 km (1)

o 5-10 km (2)

o 10-20 km (3)

o 20-40 km (4)

o More than 40 km (6)

o N/A / I don't travel for this (7)

Trip 4: Go to a doctor's appointment

For a <5km trip:

- A door-to-door DRT trip would likely cost €2.20 and take less than 15 minutes.

- A stop-to-stop DRT trip would likely cost €2.00 and take less than 20 minutes, including walk time to and from stations.

For a 5-10km trip:

- A door-to-door DRT trip would likely cost €4 and take about 15–20 minutes.

- A **stop-to-stop** DRT trip would likely cost €3.50 and take about 20–25 minutes, including walk time to and from stations.

For a 10-20km trip:

- A door-to-door DRT trip would likely cost about €5 and take about 25–30 minutes.

- A **stop-to-stop** DRT trip would likely cost about €4.50 and take about 25–30 minutes, including walk time to and from stations.

For a 20-40km trip:

- A door-to-door DRT trip would likely cost about €10 and take about 35–55 minutes.

- A **stop-to-stop** DRT trip would likely cost about €8 and take about 30–45 minutes, including walk time to and from stations.

For a 40+km trip:

- A door-to-door DRT trip would likely cost more than €12 and take longer than 55 minutes.

- A stop-to-stop DRT trip would likely cost more than €10 and take longer than 45 minutes, including walk time to and from stations.

How likely would you be to use the following DRT options for this trip, if they were available to you?

	Very unlikely (1)	Moderately unlikely (2)	Neither likely nor unlikely (3)	Moderately likely (4)	Very likely (5)	Not sure / I don't make this trip (6)
Door-to-Do or (1)	0	0	0	0	0	0
Stop-to-Sto p (2)	0	0	0	0	0	0

Attitude Qs

Section 3 (of 4)

This section will ask for your opinions on some transportation-related topics.

How much do you agree with the following statements about travel options?

	Strongly disagree (1)	Somewhat disagree (2)	Neither agree nor disagree (3)	Somewhat agree (4)	Strongly agree (5)	Not sure / does not apply to me (6)
I am satisfied with the options I currently have for day-to-day transportation. (1)	0	0	0	0	0	0
I tend to try out different modes of transportation before I settle into a particular routine. (2)	0	0	0	0	0	0
There should be more public transit options where I live. (3)	0	0	0	0	0	0

Environmental sustainability is an important consideration when choosing how to travel. (4)	ο	0	0	0	0	0
Public transit options should be promoted to reduce traffic congestion. (5)	0	0	0	0	0	0

How much do you agree with the following statements about cars?

	Strongly disagree (1)	Somewhat disagree (2)	Neither agree nor disagree (3)	Somewhat agree (4)	Strongly agree (5)	Not sure / does not apply to me (6)
Having access to a car means I can travel whenever and wherever I want. (1)	0	0	0	0	0	0
I can do things using my car that I wouldn't be able to do with public transit. (2)	0	0	0	o	0	0
Driving a car is fun. (3)	0	0	0	0	0	0

A car represents someone's position in society. (4)	0	0	0	0	0	0
Cars are a part of modern life. (5)	0	0	0	0	0	0

How much do you agree with the following statements about demand-responsive transportation?

	Strongly disagree (1)	Somewhat disagree (2)	Neither agree nor disagree (3)	Somewhat agree (4)	Strongly agree (5)	Not sure / does not apply to me (6)
I wouldn't mind sharing a trip with other passengers on a DRT minibus. (1)	0	0	0	0	0	0
I would feel comfortable using an app to request a DRT trip. (2)	0	0	0	0	0	0
If there was a reliable, wide-ranging DRT system where I live, I wouldn't need to own a car. (3)	0	0	0	0	0	0

Choosing DRT over driving would allow me to get more done while I	0	0	0	0	0	0
travel. (4)						

Demographics

Section 4 (of 4)

This section asks for some demographic information.

What is your gender?

o Male (1)

o Female (2)

o Non-binary / other gender (3)

What is your age?

o 18-24 (1) o 25-34 (2) o 35-44 (3) o 45-54 (4) o 55-64 (5) o 65+ (6)

How many people 18 years old or older live in your household?

o 1 (1) o 2 (2) o 3 (3) o 4 or more (4)

Do any young children / dependents (under the age of 6) live in your household?

o Yes (1)

o No (2)

What is the highest level of education which you have completed to date?

o No formal education (1)

o Primary education (2)

o Lower secondary (3)

o Upper secondary (4)

o Technical or vocational qualification (5)

o Advanced certificate / completed apprenticeship (6)

o Higher certificate (7)

o Ordinary bachelor degree or national diploma (8)

o Honours bachelor degree, professional qualification, or both (9)

o Postgraduate diploma or degree (10)

o Doctorate (Ph.D.) or higher (11)

How would you describe your present principal status?

o Working for payment or profit (1)

o Looking for first regular job (2)

o Unemployed (3)

o Student (4)

o Looking after home / family (5)

o Retired from employment (6)

o Unable to work due to permanent sickness or disability (7)

o Other (please specify) (8)

What is your average annual household income range?

o €24,999 or less (1)

o €25,000 - 49,999 (2)

o €50,000 - 74,999 (3)

o €75,000 - 99,999 (4)

o €100,000 or more (5)

o Prefer not to say (6)