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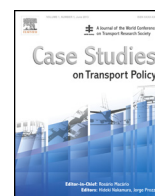
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Exploring the propensity to travel by demand responsive transport in the rural area of Lincolnshire in England



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ABSTRACT

Local transport systems in rural areas worldwide are facing significant challenges. In particular, increased car ownership and usage as well as broader socio-economic trends such as ageing populations and cuts in public spending are combining to threaten the bus – the traditional means by which people without cars have accessed the services that they need. Consequently, Demand Responsive Transport (DRT) systems have emerged in a bid to combine the benefits of bus-based and taxi-based services, to deliver a relatively cheap yet comprehensive level of public transport in low demand environments. Unfortunately, while attractive in principle, several barriers conspire to limit the effectiveness of such services in practice.

This paper therefore investigates how individual level factors influence the use of DRT systems in rural Lincolnshire in England by applying an ordered logit model to a survey of DRT users in the county. The analysis shows that those who are disabled, travelling for work, or live in less densely populated areas are likely to travel more frequently by DRT. Men are found to travel less frequently than women when they are below pension age. However there are no significant gender differences once they reach retirement age. This highlights an emerging market potential from the retired male market segment. The implications for policy include recommendations that DRT systems should be designed to cater for such market segments through both traditional channels and through further engagement with employers.

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1. Introduction

Local transport systems worldwide are facing significant challenges, many of which relate to the private car. In particular, whilst increasing car ownership and use has obviously delivered significant benefits to individuals, at the societal level it has also led to an array of economic, social and environmental impacts which require the attention of policy makers. In this regard, it should be noted that rural areas face a number of distinct challenges. Simply, Tolley and Turton (1995: 235) proposed that the basic problems can be “associated with the dispersed nature of the population and the difficulties experienced in securing acceptable levels of access to services which are only available in certain settlements”. They added that rural transport problems

had been exacerbated in many countries by the progressive withdrawal of services from smaller villages to larger settlements, and that while “the distinction between transport need and transport demand was particularly difficult to identify in a rural context”, it was vital to do so if mobility problems were to be combatted.

In the case of the UK, one major impact of rising car ownership and use in rural areas has been that the financial viability of ‘conventional’ bus services – which until now have been a key instrument in enabling those who remain without a car to access services – has been threatened in two ways. First, this has been done by directly reducing the demand for the bus and second, by contributing to more dispersed development patterns which also affect the bus operating context. Worse, while these effects are serious enough, when combined with broader socio-demographic trends (relating to the ageing population, coupled with constraints on public spending for example), they are then still further exacerbated. Consequently, ensuring that bus services remain

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accessible to the (still significant) population segment which does not have a car, is becoming increasingly difficult and expensive for public authorities to provide. Given this background, Demand Responsive Transport (DRT) is one possible solution that is being actively considered (Baker, 2011). For instance, several authorities with significantly rural hinterlands including Northamptonshire and Herefordshire have replaced subsidised bus services with DRT and Community Transport alternatives in recent years. In addition, Essex County Council replaced a rural bus service to a hospital with a shared taxi service in 2011 (Forster, 2011), while Leicestershire County Council has proposed replacing subsidised hourly bus services serving local villages with shared taxi DRT services that would need to be pre-booked (Leicester Mercury, 2012). So what is actually meant by the term DRT? For the purpose of this paper, public transport can be categorised as being Demand Responsive Transport if:

- The service is available to the general public (i.e. it is not restricted to particular groups of user according to age or disability criteria).
- The service is provided by low capacity road vehicles such as small buses, vans or taxis.
- The service responds to changes in demand by either altering its route and/or its timetable.
- The fare is charged on a per passenger and not a per vehicle basis.

Effectively then, DRT seeks to combine the benefits of bus-based and taxi-based services, in order to deliver a relatively cheap yet comprehensive level of public transport in low demand environments. Unfortunately, while theoretically an attractive proposition, DRT has still yet to reach its full potential as a mainstream mode despite an incubation period which in the UK stretches back to the 1970s (Nutley, 1988). Such a delay has been due to a wide range of practical, institutional, political, technological, social and economic barriers (see Enoch et al., 2004 for more on these), but one of the more interesting is the lack of knowledge about the likely market niches for DRT services – i.e. the types of people who might or might not use DRT should it be provided.

The purpose of this paper then, is to investigate the effect of individual level factors on the use of DRT systems in a rural context. The case study is Lincolnshire, generally regarded as one of the most mature and successful examples of DRT in the UK. Specifically it first identifies the various factors that have been found to influence the use of DRT. Second, it draws on an ordered logit model to examine how these factors affect the propensity of people to use DRT in the Lincolnshire case. Finally, conclusions are drawn, and implications for policy makers and practitioners inferred.

2. Factors affecting DRT use

In reviewing previous work identifying the factors that affect DRT use, three 'types' emerge: namely service-related or 'scheme-type' factors; area-related factors; and individual-related factors.

Looking first at service-related factors, it is evident that significant work has been applied to operational issues, for example about how to improve the efficiency of routeing, timetabling and booking methods (e.g. Chevrier et al., 2012; Lin et al., 2012), and about the role of vehicle types (Davison et al., 2012b; Enoch et al., 2004; Teal and Becker, 2011). In general, it would seem that taxis provide more cost effective DRT services in areas where demand is lowest and more dispersed, whilst minibuses (perhaps provided by social/voluntary enterprises) work better on semi-fixed route patterns in more densely populated areas, though as yet the evidence supporting this is relatively weak.

Similarly, much effort has been applied to overcoming technological issues to do with location plotting, fare collection systems and on board communication (Palmer et al., 2004; Lacometti et al., 2004). Next, Enoch et al. (2004) and Mulley et al. (2012) reported extensively on the institutional barriers faced by DRT operators. Specifically, the core problem here was due to there being such a complex array of stakeholders and regimes relating to operators, routes, vehicles and drivers in terms of licencing, tax, and insurance that many potential operators (particularly taxi firms) are put off investigating new DRT markets. Meanwhile policy factors relating to financing and subsidy, scheme objectives and motivations and decisions over eligibility criteria were discussed in Davison et al. (2012b), Enoch et al. (2004) and Mulley et al. (2012). Here, key problems were often due to poorly designed subsidy regimes, which in the case of the UK have required 'innovative solutions' to meet very specific policy objectives whilst only offering short term funds for investment as opposed to revenue support. One key lesson that emerged was that low-tech booking and routeing solutions were often appropriate for small scale DRT schemes that did not generate sufficient trips to justify the capital cost of buying a more sophisticated operations management system.

Looking at area-related factors, TCRP (1995) identified the elderly, mobility limited, and those on low incomes as potential markets, a typology which also emerged in TCRP (2004a), which noted that the typical DRT rider in rural areas and communities is likely to be "poor, elderly, or disabled" (pp. 35). Also in North America, survey results reported in TCRP (2004b) revealed that DRT was most often used in small and difficult to serve locations, though there were also examples where DRT operated in large (e.g. rural) areas, or else offered services at times of low demand. In a survey of DRT providers in Great Britain (Davison et al., 2012a), whilst rural schemes were found to not always deliver the most cost effective investment DRT on a per subsidy basis, DRT was identified by some respondents as the most cost effective way of ensuring rural communities without a conventional bus service, receive access to services, providing 'coverage efficiency'. More quantitatively, Wang et al. (2015) used a multi-level area-based analysis of data in Greater Manchester, England. The significant findings here were that demand for DRT services is higher in areas with low population density, which are predominantly white and experience high levels of deprivation. Conversely, in areas where a higher proportion of people work from home, demand is lower, which is unsurprising as working from home reduces the need to travel. The variables which were insignificant (at 95% confidence) were the proportion of population that is male and the proportion of aged 65 or over, which is more surprising as females and older people often account for a larger share of public transport users.

At the individual level, Nelson and Phonphitakchai (2012) suggested that in the metropolitan area of Tyne and Wear in the UK, the majority of DRT users are elderly female and over half are retired. It also found that most trips made are very local and do not involve a transfer and that a third of respondents require the door to door element of the service, while half need fixed arrival times at the highest level (all or most of the time). Similarly, Laws (2009) reported that the majority of users of the Wiltshire Wigglybus in the rural district of Pewsey were school children and retired people, with passengers using the service for shopping (33%), education (10%), and commuting (29%). Once again, this time in an even more rural area of Calne in the same county, she found that retired and disadvantaged users predominated, with a few commuters using the buses at peak time to get to work.

Reporting on experiences from a number of schemes across Europe, Mageean and Nelson (2003) found that females are the dominant users of the DRT services in most of the cases studied.

However, it found that average ages varied substantially, from less than 15 years in Finland right up to 77 years in Gothenburg, and noted that these age distributions were reflected in the composition of the users. Thus, two thirds of users in Belgium are retired, house persons and students; in Florence four fifths of users are unemployed or students (due to eligibility criteria); and in Campi and Porta Romana 84% of users are students and workers. Finally, Fitzgerald et al. (2000) found that increases in age and some disabling conditions reduce trips but having a sight problem increases trips while Bearse et al. (2004) found that women took about 30% more trips per month than men; and that nursing home residents took fewer trips than community residents.

In examining the current and future markets for DRT using interviews and focus groups with key stakeholders, Davison et al. (2012b) identified the existing current markets in terms of age, trip purpose and mobility but also highlighted a range of opportunities to develop the DRT market and product. Opportunities for product development included the journey to work highlighting the potential to grow the commuting market segment and for market and product development broader business travel requirements.

Finally, it is interesting that in perhaps the most comprehensive review of factors affecting public transport use conducted in the recent past, Balcombe et al. (2004) noted that “as yet, few operational results are available [relating to DRT]”, and did not report any numerical results on how demand factors and DRT use are related. Overall then, it would seem that there is relatively little quantitative information about how factors at the personal or individual level influence the use of DRT, especially in rural areas in a European setting – hence the focus of this paper.

3. Statistical model

Several statistical models have been considered in this paper to examine DRT users' propensity to travel, which is based on a customer survey conducted by Lincolnshire County Council in England. In the survey, customers were asked questions such as how often they use a DRT service, their usual travel purpose, whether they were disable, age, and gender. The customer survey will be described in more detail in the following section.

In this study, customers' 'propensity' to use DRT was modelled as the dependent variable. Since this variable is categorical and ordinal in nature (e.g. never/infrequently, once per week), it is natural to consider ordered response models such as an ordered logit model (OLOGIT) for the purpose of identifying factors influencing the propensity to travel by DRT. The OLOGIT model can be derived using a latent variable model as suggested by Long and Freese (2006). Suppose, a latent variable y^* which measures the propensity to travel as a spectrum ranging from $-\infty$ to $+\infty$:

$$y_i^* = \beta \mathbf{X}_i + \varepsilon_i$$

where \mathbf{X}_i is a vector of explanatory variables influencing people's propensity to travel – this include individual characteristics from the customer survey data as well as conditions at local areas from the UK Census data; β is a vector of coefficients to be estimated; and ε_i is the error term which is assumed to be distributed logistically. The observed propensity (i.e. weekly travel frequency by DRT) y is coded as follows: 1 = never/infrequently; 2 = once per week; 3 = twice per week; 4 = three times per week; and 5 = four times or more per week. The propensity y is determined by the value of the latent variable y^* as follows:

$$y_i = \begin{cases} 1 \text{ (never/infreq)} & \text{if } -\infty \leq y_i^* < \tau_1 \\ 2 \text{ (once per week)} & \text{if } \tau_1 \leq y_i^* < \tau_2 \\ 3 \text{ (twice per week)} & \text{if } \tau_2 \leq y_i^* < \tau_3 \\ 4 \text{ (3 times per week)} & \text{if } \tau_3 \leq y_i^* < \tau_4 \\ 5 \text{ (4 + times per week)} & \text{if } \tau_4 \leq y_i^* < +\infty \end{cases}$$

where τ_j is the cut-points (thresholds) to be estimated ($j = 1, 2, 3, 4$).

Thus the probabilities of observing each travel frequency category are:

$$Pr(y_i = 1) = Pr(y_i^* < \tau_1) = Pr(\varepsilon_i < \tau_1 - \beta \mathbf{X}_i)$$

$$Pr(y_i = m) = Pr(\tau_{m-1} \leq y_i^* < \tau_m) = Pr(\tau_{m-1} - \beta \mathbf{X}_i \leq \varepsilon_i < \tau_m - \beta \mathbf{X}_i), \quad \text{where } 1 < m < 5$$

$$Pr(y_i = 5) = Pr(\tau_4 \leq y_i^*) = Pr(\varepsilon_i \geq \tau_4 - \beta \mathbf{X}_i)$$

It can be shown that the above equations can be represented by a simple cumulative probability function:

$$Pr(y_i \leq j) = F(\tau_j - \beta \mathbf{X}_i), \quad j = 1, 2, 3, 4$$

where F is the cumulative distribution function (cdf) for ε_i and assumed logistic with mean 0 and variance $\pi^2/3$. Thus $F(\tau_j - \beta \mathbf{X}_i) = \frac{1}{1 + \exp(-\tau_j + \beta \mathbf{X}_i)}$.

The interpretation of the OLOGIT model is relatively straightforward. A positive coefficient indicates that there is higher level of propensity to travel (i.e. higher weekly travel frequency by DRT); vice versa for a negative coefficient. Since this model is a variant of a logistic model, the odds (of higher outcomes versus lower outcomes) and odds ratio – $\exp(\beta)$, can be computed to assist interpretation. Predicted probabilities at certain conditions can also be obtained, so it is straightforward to examine how probabilities of each outcome categories change with respect to changes in explanatory variables.

OLOGIT models have various limitations. Notably they assume the relationship between each pair of outcome groups is the same (i.e. the proportional odds assumption; since the coefficient does not depend on outcome categories); and also the estimations may be inconsistent with the presence of under-reporting in the data (see Yamamoto et al., 2008; Quddus et al., 2010). Various methods can be used to address the above problems such as employing a multinomial logit model (MNL) which is an unordered response models. The MNL model can be written as follows (Long and Freese, 2006):

$$Pr(y_i = j) = \frac{\exp(\beta_{jb} \mathbf{X}_i)}{\sum_{m=1}^{M=5} \exp(\beta_{mb} \mathbf{X}_i)}, \quad j = 1, 2, 3, 4, 5$$

where b is the base outcome that other outcomes are compared with; β_{jb} is a vector of injury-specific coefficients and $\beta_{bb} = 0$.

This paper will test and validate the OLOGIT model (e.g. by comparing with MNL model; see discussions below) to ensure that the OLOGIT model is valid for the data analysed before drawing any conclusions.

4. Case study area

Lincolnshire is a geographical area predominantly in the East Midlands region of England, though the unitary authorities of North Lincolnshire and North-East Lincolnshire are within the

neighbouring region of Yorkshire and the Humber. Lincolnshire County Council is responsible for transport provision across seven district council areas, namely: the City of Lincoln, North Kesteven, South Kesteven, South Holland, Boston, East Lindsey and West Lindsey. With the exception of the City of Lincoln which is classified as ‘other urban’, and Boston which is ‘significantly rural’ with between 26% and 50% of the population living in rural settlements and large market towns, all other districts are ‘predominantly rural’. Specifically, South Kesteven has between 50% and 80% of the population living in rural settlements and large market towns, while at least 80% of the population live in rural settlements and large market towns in the other six districts (DEFRA, 2011).

Lincolnshire County Council introduced the ‘CallConnect’ DRT service and brand in 2001, motivated by the need to provide improved access to people and places for a dispersed, rural population. The service has since developed over time and currently operates across most areas of Lincolnshire; the exception being in and around the city of Lincoln as the more urbanised demand profile there allows for more conventional, fixed route and scheduled buses to be operated. Two types of CallConnect services exist: semi-flexible buses between core centres, which serve main stops plus other stops on request, and area-based services. The emphasis of this paper is on the area-based services. The DRT service operates flexibly within these service areas, and additionally is fully integrated (in terms of information, timings, ticketing and places of interchange) with the ‘Interconnect’ network – which is a frequent (hourly) high quality interurban conventional bus service that provides access opportunities to the rest of the county and beyond. As well as services operating wholly within Lincolnshire, the County Council has worked in partnership with neighbouring unitary and county councils to provide a Peterborough, Rutland, Stamford and the Welland Vales cross boundary service. It also provides the booking capability for CountyConnect – a DRT service launched in nearby Northamptonshire in 2012 and which is based on the Lincolnshire model.

To use the DRT services, CallConnect customers must first register for the service. Customers can then book or request a journey by telephone, online or by SMS. Booking is available from seven days to one hour prior to the trip, and is offered on a first come first served basis. A specialist team of trained booking operatives organise journeys to optimise vehicle usage and reduce the refusal rate, where users are not able to book onto a journey which meets their needs. The services pick up from central areas in towns and villages with home pick-ups limited to more remote

rural areas and for users with a disability or impaired mobility. The vehicles used on the area-based CallConnect services are generally minibuses, which respond to the demand of the population and the geography. Both the booking process and vehicle routing and allocation are supported by Mobisoft across the area-wide services, though the final decision regarding bookings is made by an operative.

5. Data description and variable selection

The main data used in this study is from a customer survey conducted by Lincolnshire County Council in 2010. The 2010 customer survey contains responses from 432 customers in 16 different service areas. Fig. 1 below shows the spatial distribution of DRT users from the survey. The questions asked in the survey include name, address, service used (service area), trip frequency, trip purpose, booking method, satisfaction of the service, gender, age range, disability, and ethnicity.

The majority of the respondents are either “very satisfied” (62.96%) or “fairly satisfied” (19.91%) with the DRT service overall. The number of respondents, sorted by the age range and gender, is presented in Fig. 2. As can be seen, majority of the DRT users are females over 60 years old.

The reported DRT travel frequency is presented in Table 1. It is clear from the table that many DRT users travel infrequently – the “never/infrequently” category represent nearly 45% of the respondents. Meanwhile the most popular travel purpose is “shopping” (45%), which is followed by “medical appointments” (16%).

In addition to the survey data, Census data (2001) was also linked to the individual level survey data as the local context (e.g. population density, deprivation) may also affect an individual’s travel behaviour (Diez-Roux, 1998). In the UK, the Census provides a snapshot of demographic and social life across the country that helps inform government policy at local and national level. This is conducted every ten years and data is provided at various aggregate levels. In this study, Census data at the Output Area (OA) level was used, the smallest area for which the 2001 Census data is available. The OAs have an average population size of 125 households and around 300 residents. Since both the locations of the customers surveyed and OAs were available, information from both datasets could be overlaid in a GIS package, and hence the local characteristics (e.g. population density) of where each DRT customer lives could be determined.

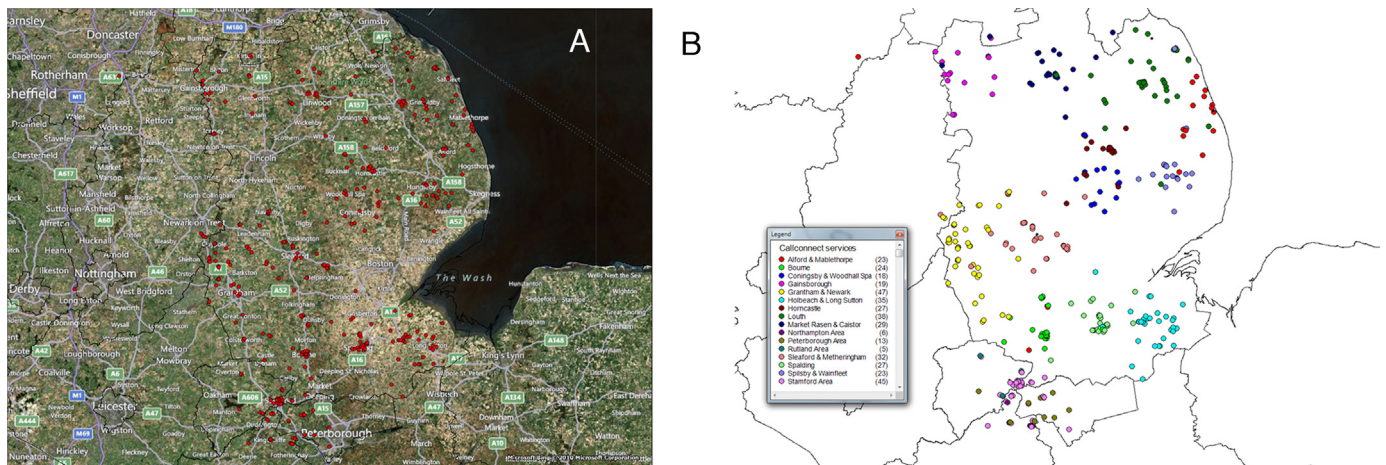


Fig. 1. Map for the Lincolnshire and the spatial distribution of DRT customers. (a) Map for Lincolnshire and surround (source: Microsoft Bing®) and customer locations (red). (b) DRT customers in different service areas. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

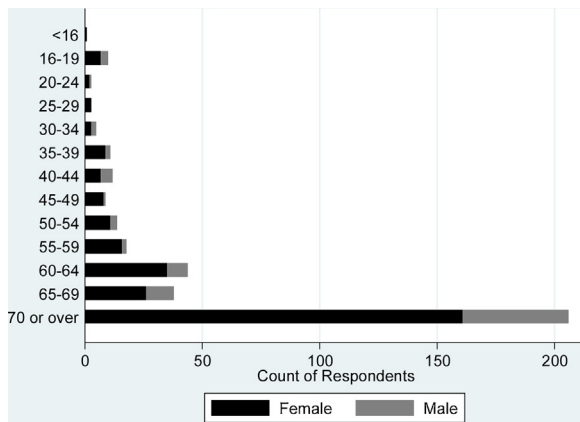


Fig. 2. Number of respondents by age range and gender.

Clearly, this nine year disparity in the age of the data is a limitation of the study, and needed to be taken into account when discussing implications and drawing conclusions. Specifically, estimates released by Government in September 2012, report that the area's population increased slightly faster than the UK average (10.4% compared to 7.9%), and that the number of people of pensionable age in particular is increasing at a faster rate than nationally (LRO, 2012). Nevertheless, the fact remains that the Census is the most comprehensive and widely available source of socio-demographic data available and hence the most appropriate to use for this study. In terms of variable selection, as discussed above, there are a number of factors that may affect an individual's propensity to use DRT, and some of these factors were available in the survey or the census data. However, not all relevant factors were included in the models because some are consistently insignificant in all models and parsimonious (i.e. simple) models are preferred. For example, in the case of "ethnicity", 96% of the respondents identified themselves as "white British". Therefore it is not surprising that this variable is statistically insignificant as there is lack of variation in the data. The summary statistics of those variables that were included in the model are presented in Table 2.

6. Modelling results

An OLOGIT model has been estimated to examine the factors affecting an individual's decision to take DRT trips. The final set of explanatory variables has been chosen empirically based on the level of statistical significance. As a result, the final model consists of all the variables presented in Table 2. Various interaction terms have also been examined and the interaction term between 'male' and 'pension age' is retained as this term is statistically significant. The modelling results of the OLOGIT model are presented in Table 3.

In order to investigate how this model would perform if different data were used (i.e. if the model was generalised), then ideally the model would be applied to external data. In the absence

Table 1
Reported travel frequency by DRT.

Travel frequency	Count	Percentage	Cum.
Never/infrequently	194	45	45
Once per week	97	22	67
Twice per week	62	14	82
Three times per week	30	7	89
Four times or more per week	29	7	96
Not answered	20	5	100
Total	432	100	

Table 2
Summary statistics of variables used in the model.

Variable	Obs	Mean	Std. Dev.	Min	Max
Travel frequency	412	2.04	1.24	1	5
Population density (people per hectare)	418	11.01	16.96	0.10	106.97
Dummy variables					
Disability	360	Disabled = 1 (124); otherwise = 0 (236)			
Trip purpose (work)	396	Work = 1 (44); otherwise = 0 (352)			
Male	380	Male = 1 (87); female = 0 (293)			
Pension age ^a	374	Of pensionable age = 1 (279); otherwise = 0 (95)			

^a 65+ for male; 60+ for female.

of such data, the 'bootstrap method' was employed instead. This is a resampling method which takes repeated random samples from the estimation sample so that standard errors and confidence intervals for the given parameters can be determined (Long and Freese, 2006), and so provides an estimate of the reliability of the model. In this case, bootstrapped standard errors and confidence intervals for the log likelihood, key parameters when measuring overall modelling performance, were calculated using 1000 replications. The standard errors and percentile based 95% confidence intervals for the log likelihood estimated are: standard error = 11.64; confidence interval = [−423.53, −378.57]. This indicates that the standard error of the log likelihood is reasonably small, suggesting that the model is relatively robust if applied to different datasets. That said, given that the sample size is relatively small ($n = 309$), it is speculated that increasing the sample size in a future study would lead to a more robust model. This model can also be validated from various aspects in terms of the underlying assumptions of the model. As discussed above, there are a number of limitations of the OLOGIT model. First, an approximate likelihood-ratio test was performed so as to compare the log likelihood from the OLOGIT model with that estimated from pooling binary logit models (Wolfe and Gould, 1998), and this showed that the OLOGIT model does not violate the proportional odds assumption (i.e. that the relationship between each pair of outcome groups is the same as assumed in the model). Second, a series of Wald tests were performed on each explanatory variable to identify how each variable varied across equations to ensure that none violated 'the proportional odds assumption' – once again, none did. Third, concerns that estimations from OLOGIT may be inconsistent with the presence of under-reporting in the data, for example that elderly people were over-represented in the sample because of them having more time available to complete

Table 3
Modelling results.

Variable	Coef.	Std. Err.	Z	Odds ratio	Percentage change in odds (%)
Population density	−0.0127*	0.0066	−1.92	0.99	−1.3
Disability	0.4276*	0.2274	1.88	1.53	53.4
Trip purpose (work)	1.3109**	0.3552	3.69	3.71	270.9
Male	−1.4085**	0.5281	−2.67	0.24	−75.5
Pension age	−0.2404	0.2924	−0.82	0.79	−21.4
Interaction term					
Male * pension	1.1845*	0.6125	1.93	3.27	226.9
τ_1	−0.3468	0.2803			
τ_2	0.6898**	0.2840			
τ_3	1.7730**	0.3052			
τ_4	2.6831**	0.3471			
Statistics					
Log likelihood	−407.0984				
Likelihood-ratio index	0.0364				
N	309				

* $p < 0.1$.

** $p < 0.05$.

survey forms, were tested. This was done by comparing the OLOGIT results with those of a standard multinomial logit (MNL) model, as these can still provide consistent coefficient estimates (except for 'constant' terms) even when under-reporting occurs (Cosslett, 1981; Yamamoto et al., 2008). In the event, it was found that both OLOGIT and MNL give similar results, e.g. population density increases people then tend to make more frequent trips. The OLOGIT and MNL models can be further compared using the in-sample predictions as shown the dot plot in Fig. 3, and so it can be concluded that the problem of under-reporting is marginal for the OLOGIT model.

Finally, potential unobserved effects needed to be accounted for, due to DRT users being grouped by defined operating areas (with associated levels of service) for example, which was done by applying a series of multilevel models (Wang et al., 2015), including both random-intercept and random-coefficient models. Fortunately, the random parameters were consistently found to be statistically insignificant, which suggests that there were no significant heterogeneity effects. Hence, the OLOGIT model used in this study seems to be valid.

In terms of the modelling results shown in Table 3, the coefficient of population density is negative and statistically significant at the 90% confidence level. For a unit increase in population density, the odds of making more frequent DRT trips are 0.99 times (or 1.3%) smaller, holding other variables constant. This means that an individual living in an area with low population density would make more frequent DRT trips. This finding is consistent with previous studies (e.g. Wang et al., 2015). The predicted probabilities with respect to population density are plotted and presented in Fig. 4 (to make the case more representative other variables are maintained as female, of pensionable age, not disabled, and trip purpose is non-working).

As can be seen in Fig. 4, there is a clear upward trend for the probability of the 'never/infreq' category as population density increases. Conversely the other categories decreased. This clearly shows that DRT trip frequency would be lower in more densely populated areas.

As for other factors, the odds of making more frequent DRT trips increase by 1.53 times (or 53.4%) for those people who are disabled compared to non-disabled. This is also expected and consistent with findings from previous studies (TCRP, 2004b). The finding for trip purpose (work) is interesting. It is found that the odds

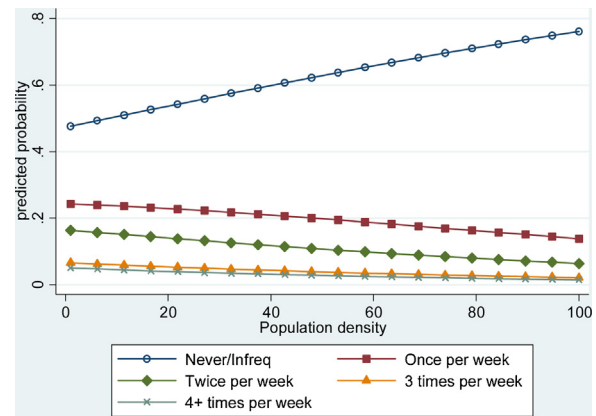


Fig. 4. Predicted probabilities with changes in population density.

of making for frequent DRT trips increase by 3.71 times (or 270.9%) for those who travel for work compared to other purposes. This is not surprising considering that working people typically need to travel on every working day, which is typically far more frequent than for other travel purposes (e.g. shopping). It should be noted that the DRT service in Lincolnshire is not just for the elderly and disabled (traditionally a significant market segment for DRT schemes in the UK), but for the public as a whole. This indicates that there may be a large potential market for the working population. Indicator variables for other trip purposes have also been tested along with work trips, but proved to be statistically insignificant.

It is found that whether a female is of pensionable age does not affect the trip frequency. However, for males, it is found that they may make more frequent trips when they are of pensionable age. Thus, the odds of male making more trips are 0.24 times (75.5%) smaller than female when they are below pensionable age. There are, however, no statistically significant differences between males and females when they are at/above the pension age (examined by a separate model in which 'pension age' was replaced by a new dummy variable standing for *not* being of pensionable age). This indicates that when men become older (at/above 65) they may become equally vulnerable as women in terms of mobility, and so they would make more DRT trips. In addition, it is also the case

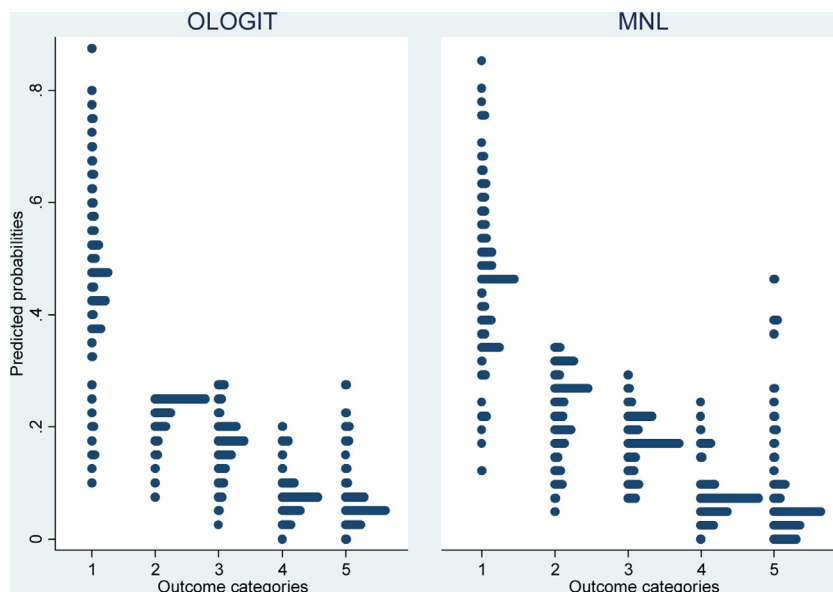


Fig. 3. Comparison of in-sample predictions between OLOGIT and MNL models.

that both men and women of pensionable age are currently eligible for free bus travel in the UK, and it may be that it is this that has a major impact on male DRT use (see later).

7. Discussion and conclusions

From previous work it is clear that females were expected to use DRT more than males (Nelson and Phonphitakchai, 2012; Mageean and Nelson, 2003; Bearer et al., 2004), and that the average age of users is usually (though not universally) higher than the population as a whole (TCRP, 1995, 2004a,b; Nelson and Phonphitakchai, 2012; Laws, 2009; Mageean and Nelson, 2003). In addition, DRT is recognised to be most effective in more rural areas both in meeting demand (TCRP, 2004a,b; Laws, 2009) and in justifying public expenditure (Davison et al., 2012a).

Looking at the Lincolnshire case, the majority of districts are predominantly rural, thus the dispersed demand creates challenges for conventional bus services. Evidence from the customer survey demonstrates a high level of satisfaction of the DRT service among a sample of current DRT users. Furthermore, the uptake of the Lincolnshire approach to DRT provision by other neighbouring authorities suggests that the County provides an example of good practice for other rural areas. With this as a basis OLOGIT models were applied to better understand how individual level factors influence the use of Demand Responsive Transport systems. Models were proven to be valid using a range of appropriate validation techniques and thus demand for DRT from a range of market segments can be quantified.

Responses to the customer survey, which provide the main data for the models, demonstrate that respondents to the survey were predominantly female and of pensionable age, which is over the age of 60 for females and 65 for males. Model results support the influence of each of these variables on trip frequency. In examining the interaction between pension and gender, to understand how demand changes over time, males reaching pensionable age are demonstrated to travel more frequently in relative terms to those pre-retirement, perhaps influenced by the current concessionary fares policy, which provides free bus travel to citizens aged over 60. When men reach the age of 65, they may also become equally vulnerable compared to female in terms of mobility. With respect to traditional markets disability was found to have a positive, significant impact upon frequency. This has implications for policy makers in that these market segments provide a core demand, which could be used as a basis for developing other markets.

Based on census data, the models also demonstrate that population density has a significant impact. Then, as population density decreases then the frequency of DRT trips increases. Hence DRT, of the model provided by Lincolnshire County Council, is of particular benefit in districts which are predominantly rural (for Lincolnshire this comprises North Kesteven, South Kesteven South Holland, East Lindsey and West Lindsey). It is worth noting that a similar trend is apparent for less densely populated segments of urban areas too (Wang et al., 2015). Therefore the implications for policy makers and practitioners are that when implementing DRT, flexible area-based systems, are most suited to less densely populated areas relative to the area as a whole.

A further significant variable influencing frequency of DRT trips is trip purpose, with respondents travelling for work purposes being more frequent users. This highlights the potential role of DRT in providing for demand from a different market segment (i.e. those in employment), thus demonstrating a market beyond the traditional dial-a-ride market (Lave and Mathias, 2000). This employment-focused segment was also identified by Davison et al. (2012b) as an opportunity for DRT product development, and given the regular nature of work trips one which can increase the

frequency of demand from a non-concessionary source. Whilst this provides possible further areas of investigation for policy makers and practitioners in the transport field, it also has broader implications for employers and employment centres. Thus, DRT could be introduced by employers to get employees to work, perhaps as part of a travel plan (see Enoch, 2012).

Finally, methodologically it could be argued that the OLOGIT model is a promising tool for assessing factors affecting individuals' propensity to travel by DRT. This survey however is limited in that Lincolnshire is predominantly rural. Also some important factors such as household income and car ownership are not controlled for in the model due to data unavailability. Thus future research could examine the effects of these factors, as well as investigating propensity to travel by DRT in other areas.

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