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An evaluation of on-demand transit user and interested-non-user characteristics and the factors that attract the transit-curious to using on-demand transit

Juwon Drake[a,*], Kari Watkins[b]

[a] *Georgia Institute of Technology, 788 Atlantic Dr NW, Atlanta, GA 30332 United States of America*
[b] *University of California at Davis, 841 Eureka Ave, Davis, CA 95616 United States of America*

A R T I C L E I N F O

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A B S T R A C T

With the advent of new mobility modes and technologies, we have seen meaningful changes in travel behavior. One such new mobility mode is on-demand transit. The Metropolitan Atlanta Rapid Transit Authority deployed its own on-demand transit system, dubbed MARTA Reach, in March of 2022. This paper provides an evaluation of the characteristics of two groups of people related to MARTA Reach: those who were interested in it and used it and those who were interested in it but did not use it. In addition, this paper explores the factors that influence membership in each of those two groups using a binary logit model, revealing the underlying characteristics that are linked with the decision to use or not use the service given prior interest. The findings show that simply providing more service has the strongest effect on adoption. Among 561 survey respondents, 426 expressed that the service area for MARTA Reach was too limited for their needs. Modeling results support this finding, in addition to the following strong predictors of on-demand transit adoption: 1) being a frequent transit user, 2) being satisfied with the current state of fixed-route transit service, 3) being part of a low-income household, 4) living within an on-demand transit service area, and 5) being younger. Understanding these group characteristics and underlying factors can help guide future efforts to provide on-demand transit service, such as by targeting the market segments that share features with the underlying factors that are shown herein to be linked with on-demand transit adoption.

1. Introduction

Sub- and *peri*-urban environments, generally a challenging place for transit agencies to provide cost-efficient service, have proven to be a hot testbed for various emerging mobility solutions, particularly on-demand transit (ODT). ODT systems operate in a broad variety of service contexts, and in North America, ODT has been used to provide first- and last-mile connections (Cordahi et al., 2018a, Cordahi et al., 2018b; Xing et al., 2022; Steiner et al., 2021) and to supplement fixed-route service, particularly during non-operating hours (Zhang et al., 2022). In Europe, ODT has been used in largely the same service contexts (Wang et al., 2014; Nelson & Phonphitakchai, 2012; Weckström et al., 2018), but with additional emphasis on providing service to outlying rural and *peri*-urban areas (Thao et al., 2023; Wang et al., 2015; Brake et al., 2004).

With the changes in travel behavior accompanying work-from-home, transit agencies must adapt their operating models to continue to provide useful service to their users. Especially important is serving those who have poor access to transit, as this segment of the population is vulnerable to social isolation and deprivation due to lack of transportation access, and thus lack of access to the social-economic systems of cities that are vital to a community's well-being. Such vulnerability can be exacerbated by the intersection of other factors, such as gender, age, race, and other socioeconomic variables. ODT has been shown to be an effective connection between areas experiencing deprivation and the respective remedial social services and opportunities (Zhang et al., 2022; Mamun & Lownes, 2011) and presents a promising solution for transit agencies to continue to serve areas, or bring new service to areas, with poor transit access. Understanding the underlying factors affecting ODT adoption will be key in further developing ODT as a useful and usual part of transit networks.

The Metropolitan Atlanta Rapid Transit Authority (MARTA) launched an ODT pilot named MARTA Reach on March 1, 2022. MARTA

* Corresponding author.
E-mail address: jdrake30@gatech.edu (J. Drake).

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Reach met the definitional criteria of ODT, also referred to as mobility-on-demand (MoD) or demand responsive transit (DRT) in other literature, set forth by Wang, et al. (Wang et al., 2014). The criteria are met as follows:

- Fare structure that charged trips on a per-passenger basis,
- Available to the general public,
- Responsive operationally to changes in demand,
- Used vehicles smaller than a typical city bus.

These criteria distinguish ODT from other modes of publicly accessible mobility that operationally resemble ODT. For example, transportation network companies such as Uber and Lyft charge fares per vehicle. Paratransit, school buses, and employee shuttles are not available to the general public and thus are not ODT. Fixed-route transit services that are allowed to deviate from their route under certain conditions to meet demand are not ODT if the vehicle used is a typical city bus or equivalent in size.

MARTA Reach operated in three service areas, later expanded to four, depicted in Fig. 1 superimposed on a map of the Greater Atlanta area. The service areas were disparate in terms of land uses, demographics, and geography. Service concluded August 31st, 2022, 6 months after the pilot began. Patrons could request a MARTA Reach vehicle using a mobile application or a phone call. A thorough evaluation was conducted, including the analysis of performance data, usage data, demographics in the service area, and user data. This last category of user data includes user satisfaction and usage pattern data that was collected using a series of custom survey instruments developed by the research team and administered through the mobile application, excepting one of the surveys which was an on-board questionnaire administered person-to-person. This survey data and the development of a binary logit model to reveal factors influencing the decision of a person who is interested in ODT to ride ODT is the subject of this paper.

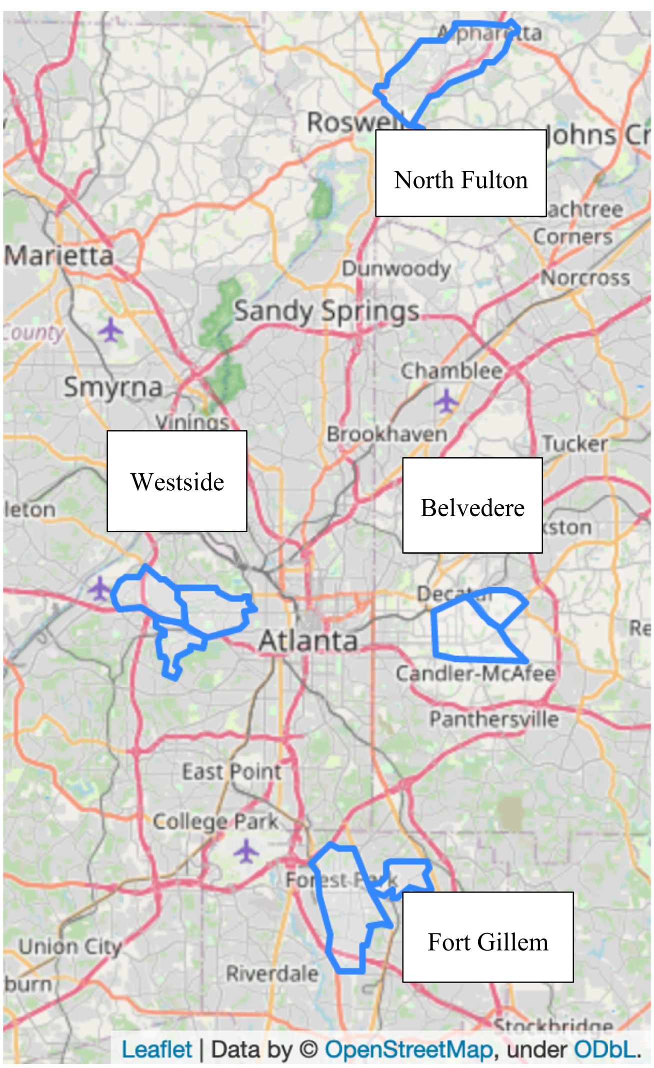

Fig. 1. MARTA Reach service areas overlaid on a map of Greater Atlanta.

This paper continues in a thread of the existing literature concerned with the satisfaction of transit users. ODT user satisfaction has been shown to drive higher ODT usage (Zhang et al., 2022), and its relationship with operational characteristics appears to be affected by intersectional factors of identity such as gender, age, and race. This paper explores the research gap in the existing literature at this meeting point of satisfaction, intersectional factors, and modeling of these factors to reveal underlying influences on ODT adoption, and presents a more precise method of revealing these influences by specifically studying the public that is already interested in adopting ODT. What factors had an influence on a person's decision to ride, or not ride, MARTA Reach, given that the person expressed prior interest in the service?

2. Literature review

Many ODT systems have existed or currently exist throughout North America and Europe, and diverse analytical methods have been applied in their evaluations. A Transit Cooperative Research Program synthesis reported on the state of the ODT practice in 2019 by interviewing 17 agencies that had provided or were currently providing ODT service and 5 agencies that were planning to provide ODT service, indicating that at least 22 of these pilots have been tried in the United States (Rodman, 2022). Consistent across North American and European contexts is the possibility of ODT trips substituting trips that would be taken on other modes, including fixed-route transit, walking, biking, and automobile (Thao et al., 2023; Haglund et al., 2019; Shamshiripour et al., 2020).

Evaluations of ODT systems in Sacramento, California, the Swiss Canton of Bern, and Belleville, Ontario, developed models to discover the factors driving ODT adoption (Xing et al., 2022; Thao et al., 2023; Zhang et al., 2022). Xing, et al. (2022), built a binary logit model estimating the likelihood of survey respondents from Sacramento, California, to be an ODT rider. The authors showed higher age, higher education, and more positive feelings about fixed-route transit were linked with lower likelihood of adopting ODT, while having a child, having a "limit [on] one's ability to drive" (Xing et al., 2022), having more positive feelings towards the local ODT service, being more sensitive to travel costs, and being more sensitive to travel time were each linked with a higher likelihood of adopting ODT (Xing et al., 2022). Thao, et al. (2023), developed a binary logit model built on survey data from the Swiss Canton of Bern and showed that younger people were less likely to use ODT, higher education was linked to higher ODT adoption, and having a public transit season pass and having access to a car were linked to a lower ODT adoption. The authors found that gender identity, being employed, and having access to a bicycle were not significant (Thao et al., 2023). Zhang, et al. (2022), distributed a survey to confirmed ODT riders in Belleville, Ontario, and used a factor analysis to reveal four latent variables: the user's satisfaction with 1) the user interface, 2) accessibility, 3) reliability, and 4) service quality. Using structural equation models, the authors found that gender identity is another significant factor, with women participating in more nighttime activities due to the availability of ODT than men. Respondent income, employment, and car access were found to be insignificant (Zhang et al., 2022).

ODT system studies in Dallas, Texas, and the Puget Sound region of Washington in the United State, Belleville, Ontario in Canada, 16 rural service areas in the United Kingdom, and the Tyne & Wear area in the United Kingdom Martin found that users of ODT services were satisfied with their experience (Martin et al., 2021; Martin et al., 2022; Zhang et al., 2022; Wang et al., 2015; Nelson & Phonphitakchai, 2012).

ODT users in Dallas, Texas, and East Gainesville, Florida, were found to be younger and to predominantly identify as black and as women (Martin et al., 2021; Steiner et al., 2021). Brake, et al. (2004), Nelson & Phonphitakchai (2012), and Wang, et al. (2015) demonstrated that ODT users on various systems in the United Kingdom also primarily identified as women, but were predominantly of older age, although much heterogeneity appears to exist in terms of the age of users.

In the same research thread as the evaluations by Xing, et al. (2022), Steiner, et al. (2021), Thao, et al. (2023), Wang et al. (2015), and Weckström, et al. (2018), this paper used user surveys distributed to those who signed up to use the service, separating them into two user groups depending on whether they did use the service, with demographic questions and satisfaction questions. The answers to the questions were processed and used as inputs in a binary logit model, also referred to as a logistic regression in this paper, to understand the factors underlying this decision of whether to use the service after signing up. This paper fills a gap in this research thread by examining interested users as a specific user group distinct from the disinterested non-user, in contrast to the evaluations by Steiner et al. (2021), Thao et al. (2023), and Wang et al. (2015), while keeping those who did not ride the service as the majority class, in contrast to the evaluations by Xing et al. (2022) and Weckström, et al. (2018). This distinction is important because it positions this study to identify the adoption factors that prevent or enable those who would like to use a service from using it, which has not been explored by the previous research in this literature review. This paper also used a user survey designed to reach respondents who did not or could not use digital media, in contrast to the evaluations by Xing et al. (2022) and Weckström, et al. (2018).

3. Methodology

Data gathering consisted of distribution of longitudinal user surveys through email and on-board. The surveys targeted people who had signed up for MARTA Reach service, and at sign-up the users provided their email addresses. The surveys are discussed further in 3.1 Surveys. Analysis and processing are discussed in 3.1.1 Processing the results. Building the binary logit model is discussed in 3.2 Modeling.

3.1. Surveys

The user surveys were developed for the two user groups of riders and non-riders in the online survey platform Qualtrics. Riders are users who completed one or more rides on Reach, where completed simply means that the rider was picked up and dropped off. Non-riders are users who registered for Reach but never completed a ride, including potential users who called a ride but canceled it. Non-riders are distinct from the general population in that definitionally the non-riders are potential users who showed some interest in the service while the general population includes both potential users and those with no interest. Five of the surveys were intended for Reach users (riders), and one of the surveys was intended for people who registered for Reach but never took a ride (non-riders). The surveys used similar style, tone, and question order and shared identical questions where comparisons were intended to be made between groups or time periods.

The rider surveys consisted of questions about mode choices, demographic information, and home addresses. Other information was gathered such as transit fare card numbers and how the respondent first learned about the service, but those data were not used in this study. Several questions asked respondents to list their origin / destination type and address and the mode the respondent would have used in the absence of MARTA Reach. User satisfaction and revealed mode choice were also variables in the surveys. These variables were selected based on significant variables found in the literature review and based on what past MARTA service quality surveys asked. The rider surveys yielded 268 valid, complete responses out of a distribution pool of 653 unique riders, for a response rate of 41.04 %.

The non-rider survey included the same demographic, mode choice, and home address questions as the but also sought insight into why the non-rider did not take a ride with Reach. The non-rider survey was distributed after the rider surveys and after the conclusion of the Reach pilot period. The non-rider survey yielded 761 valid, complete responses from a total distribution pool of 5064 potential users who had registered but not taken a trip, for a response rate of 15.7 %.

Survey uptimes are as follows. Rider surveys began on March 24th, 2022 and were available in various forms until September 23rd, 2022, 23 days after service conclusion on August 31st. The Non-rider survey was distributed to users via email on December 7th, 2022, and reminders were sent on December 12th and 16th. The response collection was concluded on February 5th, 2023.

3.1.1. Processing the results

The results were imported using Qualtrics API into Python for processing. Before the importation step, Qualtrics dropped responses that were not complete. Complete is defined as the respondent reaching the final page of the survey. Entries from the various surveys were joined using a combination of the rider IDs and the user email addresses.

The only responses that were dropped from the rider survey response set were ones with more than about 80 % of values missing or ones that could be clearly justified as being invalid responses. For the non-rider survey response set, two dropping criteria were used. Like the rider response set, if a non-rider response was missing more than about 80 % of possible values, the response was dropped. In addition to this criterion, if the respondent indicated that they had, contrary to what the rider database showed, taken a ride on Reach, their response was discarded.

Respondents were asked to provide their home address. These responses were geocoded and the home locations were grouped based on the Reach service area that they were within. An approximately 2,000-foot buffer was also applied to the service area boundaries and home locations that fell within the buffer were included in the respective service area.

A new variable was created to explain the primary mode taken to work / school that distilled the respondent's responses to the mode choice questions. The mode choice questions asked the respondent to indicate a frequency with which the respondent rides a mode. Frequencies above 4 times per week were taken as a primary mode, and then among primary modes, four broader categories and a hierarchy among the categories were established to arrive at a single primary mode category for the respondent. The four categories are the transit modes, automobile-based modes, active modes, and other modes. The hierarchy is as follows. Transit is highest, so a respondent indicating any transit mode as a primary mode was assumed to be using other non-transit modes to access transit, such as by taking rideshare to a MARTA station. Automobile-based modes are second in the hierarchy, so a respondent indicating rideshare, carpool, or private autos as a primary mode was assumed to be using modes below automobiles in the hierarchy to support automobile usage, such as by walking to a parking lot. Active modes are third in the hierarchy, so a respondent indicating bikeshare, scooter-share, biking, or walking as their primary mode would be assumed to have other, unspecified modes supporting their active mode usage. The last mode category in the hierarchy is the other category, which is simply the "other" option which also allows user elaboration of what that other mode is through free-form input on the survey.

One question had variables that were manually re-encoded using respondent free-form responses. A question on the non-rider survey asked respondents to indicate why they had not taken a ride with Reach. The question had an "other" response category that allowed freeform input. If appropriate, the "other" responses were manually re-encoded to an existing category or to one of four added categories which emerged during manual re-encoding. Altogether, 126 responses to this question were re-encoded.

3.2. Modeling

Using the collected survey data, a binary logit model was built to estimate the likelihood that a respondent would be a "rider" or "non-rider". Questions about demographics, overall MARTA service satisfaction, length of MARTA usage, home address, and frequency of usage of transportation modes were identical or asked with minor modification across the rider and non-rider surveys. Because of this equivalence, the responses could be used as classification model input variables across the two classes with little to no manipulation.

The datasets used for modeling were built on the demographic and geographic, MARTA satisfaction and length of usage, and modes responses for each respondent. Respondents either belonged to class "rider" or "non-rider". The variables were variously encoded and re-encoded, and several different combinations of variable encoding strategies were explored, with model performance, conceptual consistency, and model interpretability as the primary concerns when choosing the appropriate encoding schema. Variables were dropped based on high collinearity with other variables, or, during model refinement, based on insignificance. The data encoding, model refinement, and results are presented in greater detail in 5 Modeling Results.

4. Survey results

4.1. Rider surveys

The participation rates for each survey instrument are shown in Table 1.

4.1.1. Respondent characteristics

Rider respondents were predominantly younger than 44 years old, with 70.4 % of respondents falling into that category, while for non-riders the proportion was 54.9 %. The largest age group among riders was the 25 to 34 group, comprising 30.3 % of respondents. 50.4 % of rider respondents have at least a bachelor's degree, while that proportion for non-riders is 67.8 %. Note that 97.68 % of riders and 98.3 % of non-riders responding reported having completed high school. Men and women comprise an even split of the respondents among riders, with each having 47.9 % of the share of respondents, while slightly more men are non-rider respondents than women, at 48.0 % and 45.3 %, respectively. 2.9 % of rider and 2.7 % of non-rider respondents either declared non-binary gender or self-described their gender. 58.5 % of riders and 34.6 % of non-riders responding identified as black, while 23.8 % of riders and 43.9 % of non-riders identified as white. These statistics are shown in Table 2.

56.7 % of rider respondents were in the "Low" household income category, meaning that their household's income is less than $49,000 per annum, while that proportion for riders was 30 %, shown in Fig. 2.

Respondents provided the location of their home address, and the results were geocoded and mapped. A buffer of approximately 2,000 feet captured home addresses close to zones but not within zones. 14 % of riders and 12.3 % of non-riders who were classified as out-of-zones were reclassified as within zones with the buffer. After buffering, 18.1 % of riders and 70.5 % of non-riders lived outside of zones. Fig. 3 shows the reclassified home address counts in each zone. Notice that Fort Gillem Phase 1 is not listed, as no respondents reported a home address within that zone. Fig. 4 shows the number of users and non-users in each zone on a map of Atlanta, with the zone boundaries outlined in blue.

Table 1
Participation number and rate for each of the three main survey instruments.

Survey instrument(s)	Unique respondents	Participation rate
Non-rider survey	761	15.70 % (N=5064)
Rider surveys	268	41.04 % (N=653)

Table 2
Proportions of riders and non-riders for various demographic variables.

Variable	Riders	Non-riders
Younger than 44 years old	70.4 %	54.9 %
Hold at least a bachelor's degree	50.4 %	67.8 %
Men	47.9 %	48.0 %
Women	47.9 %	45.3 %
Non-binary	2.9 %	2.7 %
Black	58.5 %	34.6 %
White	23.8 %	43.9 %
Asian	5.38 %	7.81 %
Hispanic or Latino	5.38 %	5.86 %

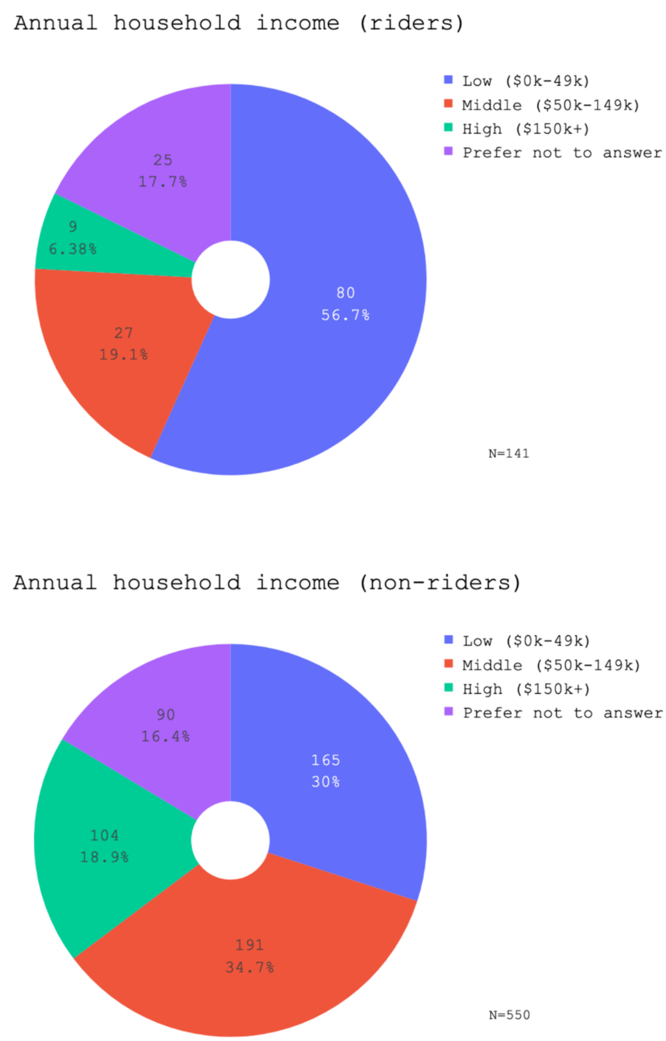

Fig. 2. Annual household income of riders and non-riders.

4.1.2. Transportation usage and satisfaction

Respondents were asked to report how often they use each of several modes. The modes were aggregated into the four categories of Transit, Auto, Active, and Other, and the frequency of mode usage was ranked to arrive at a primary mode for each respondent. See 3 Methodology for further discussion on the primary modes. Before the introduction of Reach, rider respondents were primarily transit users, with 78.5 % of respondents reporting using transit often to get to work or school. After the introduction of Reach, respondents were primarily Reach users, at 60 % of respondents. Reach being the most common primary mode does not rule out the possibility of multimodality of Reach trips. The primary

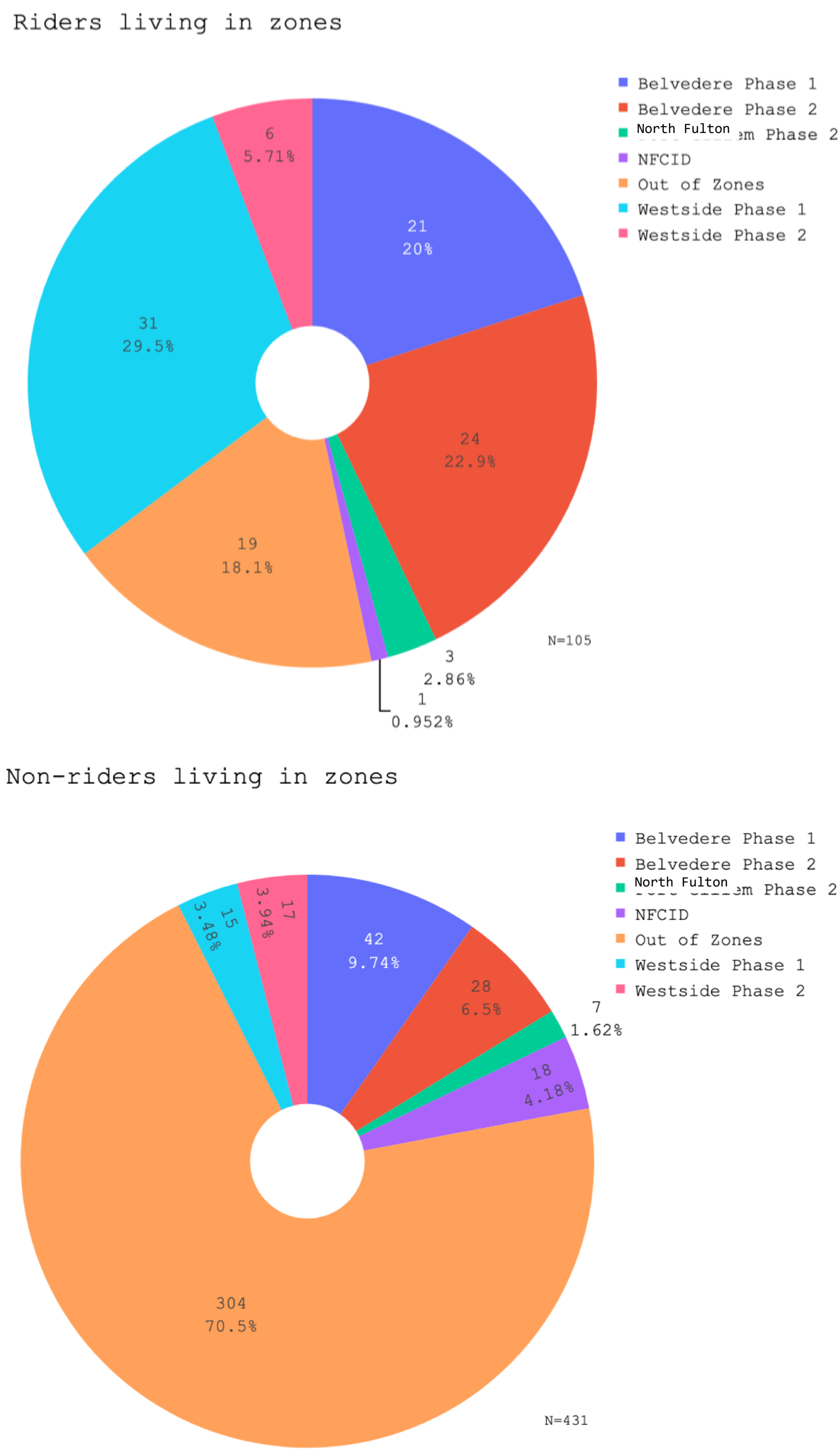

Fig. 3. Location of respondent home address in MARTA Reach zones with zone buffer applied.

mode simply indicates what mode the respondent uses predominantly.

The largest share of non-rider respondents are primarily transit users, and the second largest share are primarily automobile users, with 45.7 % and 44.3 % of non-riders in each category, respectively.

75.3 % of rider and 47.6 % of non-rider respondents are at least satisfied with MARTA services overall, including fixed-route bus and rail, and flexible route paratransit, while 11.34 % of riders and 23.6 % of non-riders are dissatisfied or very dissatisfied, as shown in Fig. 5.

Major differences appear to exist between riders and non-riders in all variables explored in this section except in terms of gender identity. The

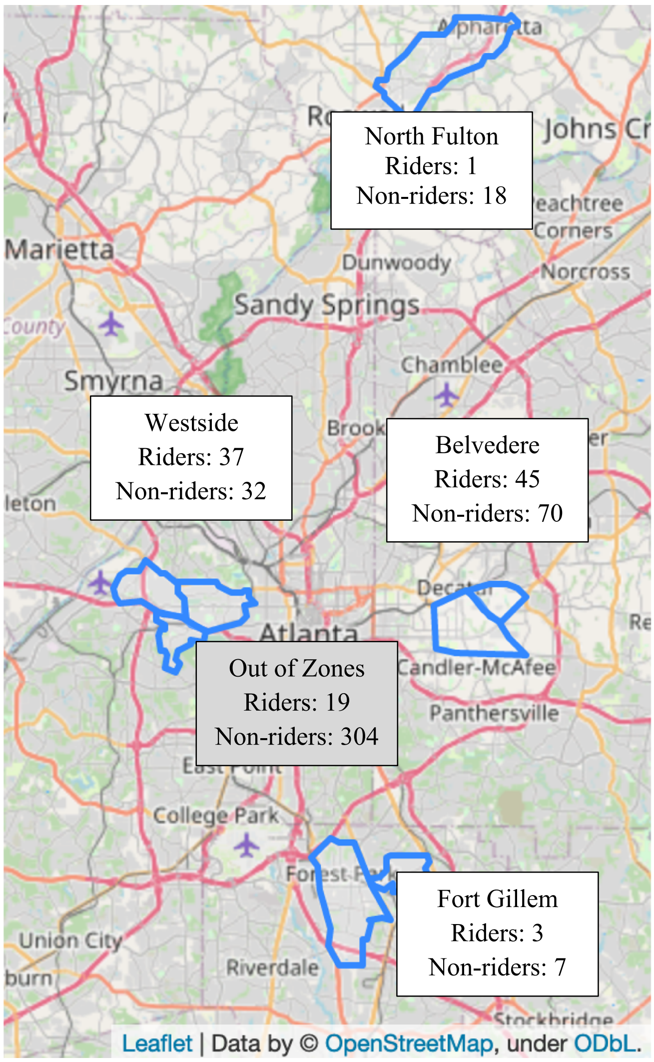

Fig. 4. Location of respondents mapped according to Reach zone, with zone boundaries in blue.

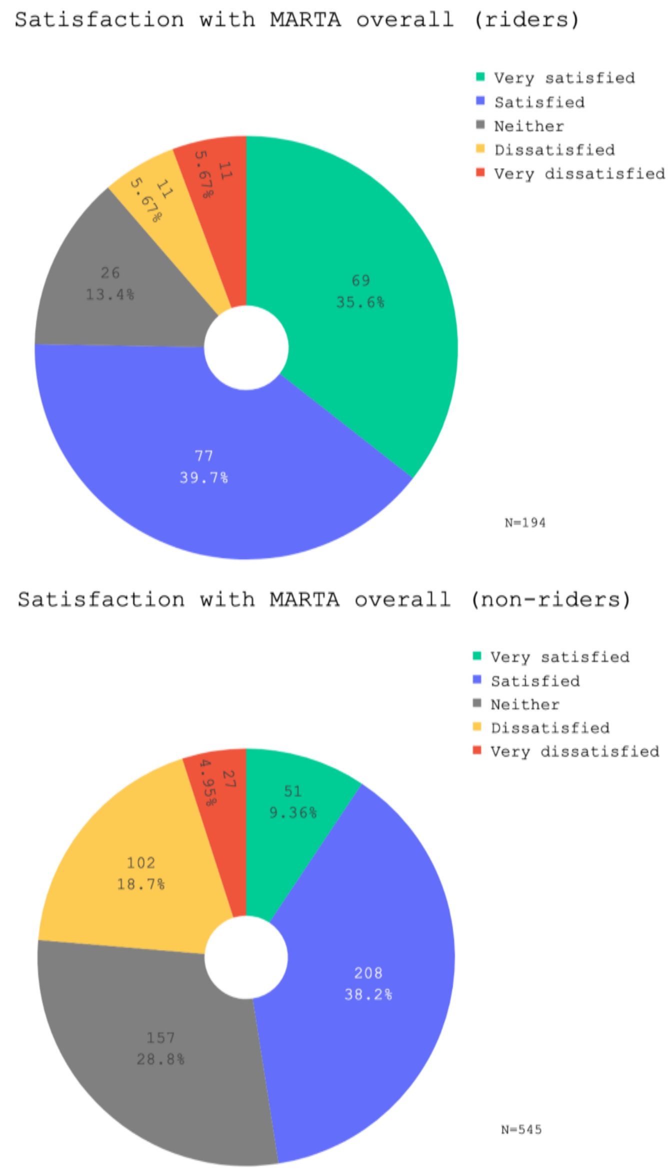

Fig. 5. Satisfaction with MARTA services overall, including fixed route.

following chapter, 5 Modeling Results, explores these differences further and develops a logistic regression to reveal the underlying factors in ODT adoption. See 6 Discussion for further discussion on the survey results, modeling results, and interpretation of each.

5. Modeling results

To build the modeling datasets, the demographic and geographic, MARTA satisfaction and length of usage, and modes responses were extracted from each of the rider and non-rider groups. The target variable, "rider", was created and responses from the rider surveys were labeled "rider", while responses from the non-rider survey were labeled "non-rider". All responses were concatenated into a single dataset with the target variable, "rider", as a column. The variables were then encoded according to the data type. Two discrete numerical variables number of people in the household and number of children in the household were among the inputs, but the remaining variables were all ordinal or nominal categorical data. The nominal variables were encoded using the "dummy variable" method and the index variable removed from the variable set. Ordinal variables were given codes from 0 to the number of categories. Missing data was not re-encoded in any way and entries containing missing values were removed from the dataset all responses containing null values were dropped, and the split of riders versus non-riders used in the model was 406 non-riders and 69 riders out of 475 total respondents. These 475 were the respondents who had responded to all the questions used for modeling.

Input variables were examined in a correlation matrix after encoding but before dropping the index variable from the dummy variable-encoded nominal variables. Some variables showed high correlation with each other and were dropped. Fig. 6 shows the correlation matrix before any variable dropping or re-encoding. High correlation is depicted by darker red or blue, depending on whether the correlation is positive or negative, respectively.

The gender variable was simply re-encoded as a Boolean variable indicating whether the respondent is a woman or not. Race / ethnicity was re-encoded as a Boolean variable indicating whether the respondent is white. The service area variables, which are Belvedere Phases 1 and 2, Fort Gillem Phase 2, North Fulton, Out of Zones, and Westside Phases 1 and 2, were re-encoded as a Boolean variable indicating whether the respondent lived out of zones or not. The primary modes variable was re-encoded to indicate whether the respondent primarily takes transit to work or school. After this re-encoding, the dataset used in the logistic regression consisted of 11 input variables and the one target variable. Table 3 shows the variables along with their variable type and a detailed description of how the variable is coded and what it represents.

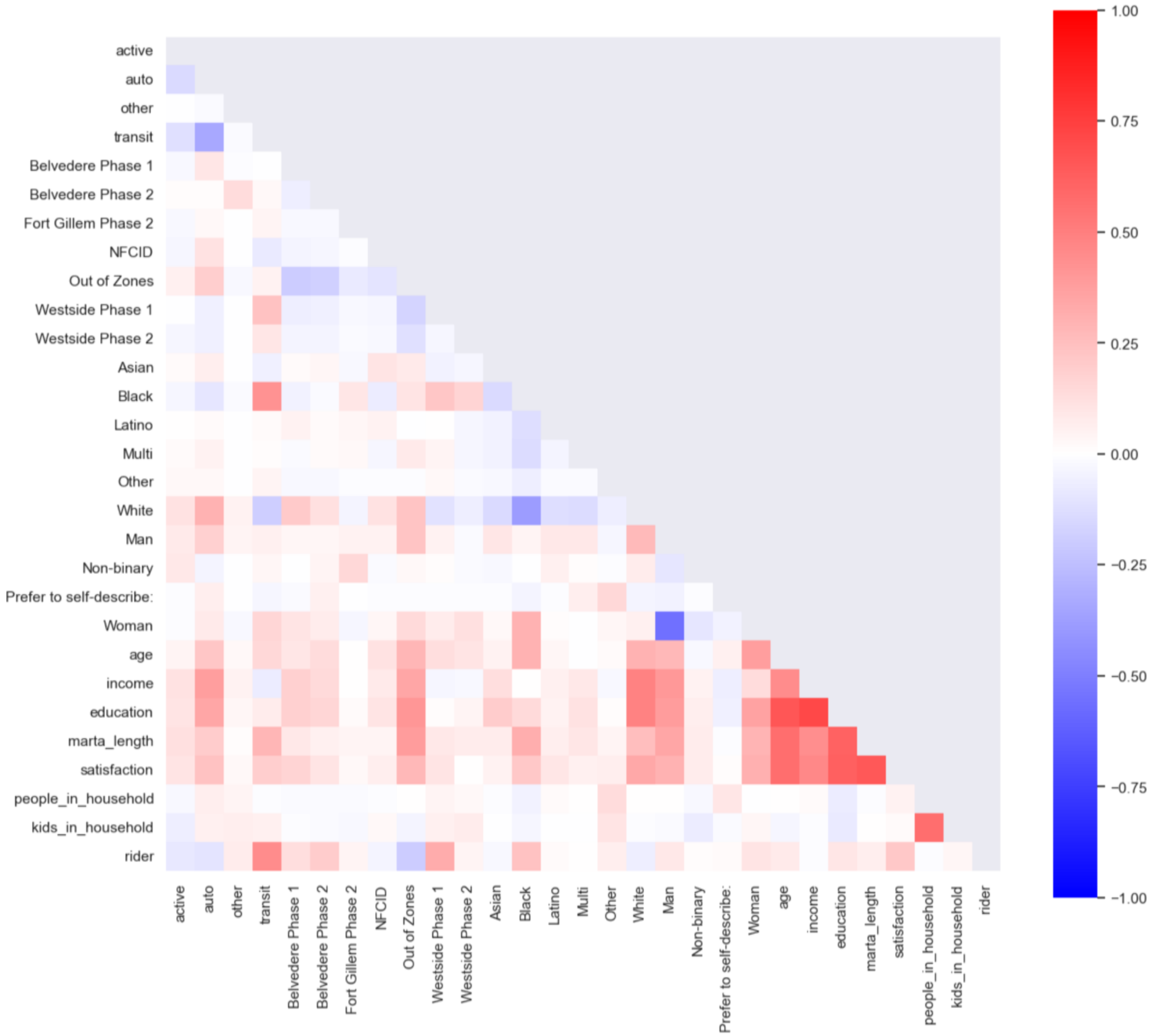

Fig. 6. Correlation matrix before dropping and re-encoding variables.

5.1. Logistic regression

The logistic regression model implementation used was from the "statsmodels" Python package. By default, the package uses Newton's method, also called Newton-Raphson, for numerical optimization. The results from the initial model specification are presented as follows. The optimization converged in eight iterations. McFadden's likelihood ratio index, henceforth called the pseudo-R^2, is 0.3242. The log-likelihood is 133.02, the null log-likelihood is 196.84, and the p-value of the likelihood ratio test is 5.202e-22, indicating that the model predicts the target variable significantly better than the null model.

The coefficients, standard errors, and significance of each variable are shown in Table 4. Note that the constant, age, being a transit user, living outside of a service area, and overall satisfaction with MARTA services appear to be significant in the model. The signs of the coefficients are consistent with what was expected for the significant variables. See 6 Discussion for further elaboration on the model coefficients, the revealed influential factors in ODT adoption, and other aspects of this model and subsequent model specifications developed from it which are discussed later in this section. Notice that neither age nor income are significant.

Also notice the coefficients and signs of the number of people living in the respondent's household and the number of minors living in the respondent's household. The coefficients are close in magnitude and opposite in sign, and both variables have the same unit and same order of magnitude. A collinearity problem could exist between these two variables. Combined with what the coefficients show, the case for dropping one of the two becomes clearer, and the number of people in the respondent's household is dropped in subsequent model specifications as it is less significant.

Adjusting the ordinal variables to be represented by dummy variable-encoded nominal variables resulted in better model performance, as measured by pseudo-R^2. The highest performance gain came from adjustment of the income variable. Adjusting other variables, such as encoding the education variable as a dummy variable, either did not result in a high enough performance gain to justify the change or did not lead to any new significant variables being formed. As such, the income variable was re-encoded to consist of nominal categories "low-income",

Table 3
The 11 input variables for modeling with their type and description.

Variable name	Type	Description
transit	Boolean	True if respondent uses transit as primary mode to work and/or school
outside_zone	Boolean	True if respondent's home address is more than 2000 feet away from a Reach service area
white	Boolean	True if respondent identifies solely as white
woman	Boolean	True if respondent identifies as a woman
age	Ordinal	6 age categories, with higher values for categories representing higher age
income	Ordinal	13 household income level categories, with higher values for categories representing higher income
education	Ordinal	6 education level categories, with higher values for categories representing more years in education
marta_length	Ordinal	4 MARTA riding history categories, with higher values for categories representing longer and more frequent riding
satisfaction	Ordinal	5 levels of satisfaction, arranged similarly to a Likert-type scale, centered on a neutral category
kids_in_household	Discrete	Numerical input for number of persons under the age of 18 in the respondent's household
people_in_household	Discrete	Numerical input for number of persons in the respondent's household

Table 4
Logistic regression coefficients with sample size (sum of rider and non-rider respondents), standard errors, and significance codes for initial and final model specifications.

Variable name (N=475)	Initial model specification coefficient	Final model specification coefficient
Constant	2.7369* 1.145	3.0605*** 0.544
Transit user	2.2759*** 0.437	1.9153*** 0.361
Lives outside service area	2.4008*** 0.404	2.2450*** 0.386
White	0.1199 0.39	N/A
Woman	0.2563 0.346	N/A
Age	0.3463 0.132	0.3233** 0.122
Income	0.0696 0.057	N/A
Low income	N/A	0.6279° 0.349
Education	0.2392 0.2	N/A
Length of MARTA ridership	0.0471 0.293	N/A
Overall satisfaction with MARTA	0.6997*** 0.164	0.6652*** 0.159
Number of minors in household	0.1962 0.155	N/A
Number of people in household	0.1929 0.22	N/A
McFadden's pseudo R^2	0.3242	0.3209
Log-likelihood	133.02	133.67
Null log-likelihood	196.84	
p-value of likelihood ratio test	5.20E-22	1.42E-25

Significance codes: *** 0.001, ** 0.01, * 0.05, ° 0.1

"middle-income", and "high-income", with the thresholds being those making below \$50,000 per year, those making at least \$50,000 and below \$150,000 per year, and those making at least \$150,000 per year, respectively. The middle- and high-income dummy variable were dropped, and the low-income variable retained.

The removed variables in the final model specification are identifying as white, identifying as a woman, education, length of MARTA ridership, and number of minors in the household. The resulting model has a small decrease in pseudo-R^2 compared with the previously specified model, with the new pseudo-R^2 being 0.3209.

All coefficient signs and magnitudes are within the realm of what would be expected. Notice that having low income is not significant in this model. Further discussion of the 11 variables explored, the different model specifications, and what they mean in the context of this pilot and future ODT service are in 6.2 Rider or non-rider.

6. Discussion

6.1. Characteristics of riders and non-riders

Overall, riders tended to be younger, had less education, lower income, and were more likely to identify as black than non-riders. Those in the older age groups were more likely to be non-riders, while those in the younger age groups were more likely to be riders. 355 out of 524 non-riders (67.7 %) have graduated college, while 66 out of 129 riders (50.4 %) have done the same, for a difference of 17.3 % between the two groups. Little difference exists between the gender distribution of the groups. Both displayed a roughly even split between men and women, while those with non-binary and self-described genders were not well-represented. The differences between the two groups in household income and race / ethnicity are much more pronounced than for the other demographic characteristics. Most rider respondents came from low-income households, at 80 out of 141 (56.7 %), and the majority identified as black, at 76 out of 130 (58.5 %) of respondents. Compare these figures to those of non-riders, with 165 out of 550 (30.0 %) respondents reporting coming from a low-income household, and 177 out of 512 (34.6 %) respondents identifying as black. 225 non-rider respondents identified as white (43.9 %), which is a significantly higher proportion of respondents than the 31 out of 130 (23.8 %) riders who identified as white.

Riders also were more likely to use transit modes as a primary mode to access work / school, less likely to be infrequent riders of MARTA and more likely to be frequent riders, and more satisfied with overall MARTA service than non-riders. 51 out of 65 rider respondents (78.5 %) reported riding transit at least 4 times per week to access work / school prior to the introduction of Reach. Compare to 203 out of 437 (46.5 %) non-rider respondents reporting taking transit at least 4 times per week to access work / school. 75 out of 106 (70.8 %) of rider respondents characterized their MARTA riding habits as long-term frequent riding, while 255 out of 598 (42.6 %) of non-rider respondents characterized their riding habits in the same way. Possibly related to this trend is the lower reported satisfaction among non-riders, with only 56 out of 576 responding non-riders (9.7 %) indicating very high satisfaction with overall MARTA services. Contrast this satisfaction rate to responding riders, of which 69 out of 194 (35.6 %) indicated very high satisfaction. 172 out of 194 rider respondents (88.7 %) reported feeling at least neutral about overall MARTA service, while 440 out of 576 non-rider respondents (76.4 %) had the same feelings. The difference in these figures is not as wide as for very high satisfaction, indicating that all users were likely to at least have neutral feelings, i.e., *not* harbor negative feelings, about MARTA. The broader implication could be that to even be interested enough to sign up for Reach, a potential user must at least feel indifferent towards MARTA, and a negative opinion about MARTA would likely lead to a potential user not being interested in new MARTA service.

6.2. Rider or non-rider logistic regression

6.2.1. Significant variables

Table 4 presents the coefficients, standard errors, and significance of each of the five significant variables identified while building the rider / non-rider logistic regression model. Table 5 shows the model with Euler's constant exponentiated using the model coefficients, which provides the change in odds ratio of success to failure per unit change in

Table 5
Five-variable model with exponentiated Euler's constant using model coefficients.

Variable name	Coefficient	Odds ratio e	Inverse odds ratio $\frac{1}{e}$
Constant	3.0605	0.0469	21.3382
Low income	0.6279	1.8737	0.5337
Overall satisfaction with MARTA	0.6652	1.9449	0.5142
Transit user	1.9153	6.7890	0.1473
Lives outside service area	2.2450	0.1059	9.4404
Age	0.3233	0.7238	1.3817

the variable, making the coefficient more interpretable. Note that an odds ratio of 1 corresponds to 50 % probability for both success and failure. Specifically in this model, success and failure refer to being a rider and being a non-rider, respectively. Therefore, odds ratios with values less than 1 correspond to a *decrease* in the odds of being a rider versus the odds of being a non-rider per unit change, while an odds ratio value greater than 1 corresponds to an *increase* in the odds of being a rider versus the odds of being a non-rider per unit change. In other words, an e less than 1 is the result of a negative coefficient , while positive coefficients have e greater than 1, where e is the odds ratio and is the log-odds, the coefficients in the model. The inverse odds ratio provides the change in odds with respect to being a non-rider per unit increase in the variable.

Examining the odds ratios, the "transit user" variable stands out as strongly affecting being a rider. Recall that "transit user" is a binary Boolean variable indicating whether the respondent uses transit at least four times per week to access work or school, and potentially taking multimodal trips involving transit. Previously, this usage pattern was defined as the respondent's "primary mode", and the transit user variable indicates whether the respondent's primary mode is transit. As such, this odds ratio can be interpreted to mean the following: holding all other variables constant, a potential Reach user who also uses transit as their primary mode of transportation has 579 % (5.79 times) higher odds of becoming a Reach rider than a potential Reach user who does not use transit as their primary mode of transportation.

Examining the inverse odds ratios, the "lives outside service area" variable appears to have a strong effect on being a non-rider. Recall that "lives outside service area" is a binary Boolean variable indicating whether the respondent lives outside of a Reach service area plus a 2000-foot buffer to capture respondents close to a service area. The inverse odds ratio can be interpreted to mean that with all other variables held constant, a potential Reach user living outside of a service area has 844 % (8.44 times) higher odds of being a non-rider than a potential Reach user living within a service area. The converse of the inverse of this odds ratio can be expressed to make clearer the strong effect residing within a service area has on user behavior: a potential Reach user living within a service area has 844 % (8.44 times) higher odds of being a rider than a potential user living outside of a service area. Note that these findings cannot support a conclusion such as "if you build it, they will come" or any other broadly-based statements about travel behavior within a population, as all respondents were *at least* interested enough in Reach to sign up for the service *and* complete a survey. However, although the data and model are limited in this way, the non-rider market is potentially quite large, as partially evidenced by the imbalance between the rider and non-rider classes, with riders representing only 14.5 % of respondents. Put another way, only 14.5 % of potential users who were interested enough in the service to sign up and take a survey tried riding Reach, indicating the presence of a substantial number of non-riders who could be converted to riders through expanded service.

"Low income" is the weakest of the three binary Boolean variables, and indicated whether the respondent's household makes below $50,000 per year. The odds ratio can be interpreted to mean that a respondent has 187 % (1.87 times) higher odds of being a rider, all other variables kept constant, if they are in a low-income household.

"Overall satisfaction with MARTA" and "Age" are ordinal categorical variables, and the coefficient can be multiplied by the category code, causing the variable to behave nominally similarly to a discrete variable. "Overall satisfaction with MARTA" indicates the respondent's satisfaction level with all MARTA services, including but not limited to bus, rail, and paratransit. The satisfaction categories are coded from 0 to 4, with 4 representing the highest satisfaction level and 0 the lowest. The odds ratio can be interpreted to mean that with each jump to a higher satisfaction category, the respondent has 95 % higher odds of being a rider than of being a non-rider, all other variables kept constant. Thus, a satisfaction in the 4th category representing highest satisfaction would mean the respondent has 678 % (6.78 times) higher odds of being a rider than of being a non-rider, all other variables kept constant. This finding may suggest that Reach did not bring in new riders to the MARTA system overall and may not have the potential to do so. The "Age" variable behaves similarly but in the opposite direction, causing respondents to have a higher likelihood of being non-riders the higher among the categories to which the respondent belongs. Age is coded from 0 to 5, with 5 representing those 65 and older and 0 representing those 18 to 24 years old, with roughly equally spaced categories between them. Moving up one category in age leads to 38 % (0.38 times) higher odds of being a non-rider than of being a rider, all other variables held constant. At the 5th category, the respondent would have 591 % (5.91 times) higher odds of being a non-rider than of being a rider. Differences with European ODT evaluations that showed that higher age is linked with higher rates of ODT riding (Thao et al., 2023; Wang et al., 2015; Brake et al., 2004; Nelson & Phonphitakchai, 2012) may potentially be attributed to several factors, such as lower feelings of safety and higher technological barriers (i.e., calling a ride over the phone may not have been as convenient or as well-advertised as using the mobile app) in the MARTA Reach context and generally in the North American context.

The coefficient of the constant, and the calculated inverse odds ratio, indicates that at a baseline, potential users have much higher odds of being a non-rider. With all other variables held constant, a potential user "starts with" or "naturally has" 2034 % (20.34 times) higher odds of being a non-rider. This very high inverse odds ratio indicates the possibility of a strong bias against taking Reach among respondents but may simply be an effect of the imbalanced classes and the relative rarity of being a rider.

6.2.2. *Insignificant variables*

Several variables turned out to be insignificant, contrary to findings from previous experiences with ODT and/or contrary to intuition. Recall that the variables "White", "Woman", "Education", "Length of MARTA ridership", and "Number of minors in household" were not significant in the model specified just prior to the five-significant-variables only model. "White" and "Woman" were binary Boolean variables. "White" indicated whether the respondent identified as white, while "Woman" indicated whether the respondent identified as a woman. Through this binary categorization, white and women represented the respondent's race / ethnicity and gender identity. In past experiences with ODT, both race and gender, especially identifying as white (Wang et al., 2014) or black (Martin et al., 2021; Steiner et al., 2021) and identifying as a woman (Wang et al., 2015; Wang et al., 2014; Brake et al., 2004; Zhang et al., 2022; Martin et al., 2021; Steiner et al., 2021), were significant factors in ODT adoption.

Education was also found to be significant in ODT adoption in two other evaluations of an ODT systems explored in 2 Literature Review. The Ebuxi evaluation by Thao, et al. (2023), found that better educated people were more likely to adopt ODT, possibly because of a greater understanding of the negative effects on climate change that transportation can have (Thao et al., 2023). However, in this paper, education was not significant, similarly to what was found in the SmaRT Ride evaluation (Xing et al., 2022). Race / ethnicity, being a transit user, and income all had modest correlation to education. Education was possibly the weakest variable among these other variables and simply was "robbed" of its power by the others.

"Length of MARTA ridership" and "Number of minors in household" could be reasoned to influence ODT adoption but were insignificant in the model. Length of MARTA ridership is modestly correlated with being a transit user according to the correlation matrices, and in theory the two variables are measuring the same travel behavior the degree to which the respondent is dependent or reliant on transit, or the degree of the frequency with which the respondent chooses to use transit but from different perspectives. Due to this similarity, the length of MARTA ridership variable likely was "overpowered" by the variable directly measuring transit usage. The number of minors in household had no similar variable remaining after the number of people in household was dropped from the models. The insignificance of this variable could be explained by the lack of variable directly measuring access to an automobile. Likely, those with access to a car *and* children were not likely to use ODT, but those without access to a car are not affected in terms of their ODT adoption by having children. The insignificance of the number of minors in household contrasted with the significance of the variable in the SmaRT Ride evaluation (Xing et al., 2022), but that study asked about children younger than 6, whereas the surveys developed for this paper asked about minors younger than 18. Possibly, had the age cutoff been lower, the variable would have been significant like in the SmaRT Ride evaluation.

Several differences between this evaluation and past evaluations could exist due to differing cultural and historical contexts between Europe and North America or between Atlanta and other areas of the United States. Variables such as race / ethnicity, education, and gender appear to behave significantly differently depending on the local context.

7. Conclusion

This paper studied the factors influencing ODT adoption and the characteristics of ODT riders and interested-non-riders. Using data collected from a series of surveys, the characteristics of each group were obtained and analyzed. These characteristics were used to build a binary logit model estimating the likelihood of the user being a rider or a non-rider. ODT riders were found to be younger, low-income transit users who are very satisfied with MARTA service and live inside of a Reach service area, while non-riders were found to be middle- or high-income automobile users and transit users who feel neutral about MARTA service and live outside of a Reach service area.

7.1. Shortcomings and future research

This paper did not directly ask respondents to indicate their level of access to an automobile. While this omission was intentional in the survey design, analysis revealed that access to an automobile was possibly a latent variable and may have improved model fit had the variable been explicit. However, Wang, et al., found that variables like income and education are highly correlated with access to a car (Wang et al., 2014). Future evaluations attempting to classify users based on ODT adoption should include an automobile access variable.

Furthermore, this evaluation limited itself in scope to people who were interested enough in ODT to sign up for MARTA Reach. Essentially, the population can be characterized as falling into three groups: 1) the riders and 2) non-riders, also referred to as the users in this study and of which the respondents are a subset, and 3) the potential users, who are the people who did not sign up for Reach. These "uninterested masses", the complement of those who signed up, were not part of this evaluation in any way. This design was intentional, as the potential user group is far larger than the users, are highly heterogenous, and would likely need to be further segmented to be an effective part of an ODT evaluation, and the data, human, and computational resources did not exist to undertake this further analysis. Future studies that have access to data from a non-rider group and have the resources to undertake analysis of the wider uninterested population should do so, as this group could reveal insights into what factors affect *interest* in ODT, rather than just *adoption given interest*.

An additional shortcoming is the small sample size used in modeling. Future research may consider mitigating strategies, such as encoding missing data, or enforcing question answering within surveys. These strategies will allow future researchers to retain more responses which this paper dropped due to missing data.

7.2. Impact and context

The findings from this study are important to understanding factors that affect ODT adoption among ODT-interested populations in similar social-cultural and place-contexts to that of the Greater Atlanta area. Over-generalizing or over-simplifying the specific applicability of the findings would be hazardous, as transit systems operate in a highly human context. This paper and the evaluations referenced here are not necessarily repeatable experiments but momentary glimpses into a complex system of human need, desire, and its fulfillment or lack thereof. That said, as studies evaluating ODT in multiple regions are conducted, patterns of usage can appear and better support future efforts to implement such services.

ODT has the potential to play a key role in bringing back riders to transit systems recovering from the COVID-19 pandemic and to better serve places with poor fixed-route coverage. What has been shown here is that ODT may have great potential for expansion and adoption among the transit-riding public in Greater Atlanta. Those who rode the service expressed highly positive sentiments about it and planned to ride more frequently. The non-riders overwhelmingly did not ride simply because the service was not available in their area. The findings here also affirm that ODT adoption factors are considerably different across contexts, spatially, temporally, socially, and culturally. In terms of ODT's ability to attract new transit users, the findings here shows that regular transit riders will take ODT instead of other modes, including private automobiles, but that people who have never used transit before are unlikely to be attracted to it because of the presence of ODT. Note that this potential for opening new markets may exist, and the study was not designed to show it, but the data here cannot support such a claim. However, ODT is a mode that shows great potential for making transit more attractive and useful.

CRediT authorship contribution statement

Juwon Drake: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Resources, Software, Validation, Visualization, Writing original draft. **Kari Watkins:** Conceptualization, Funding acquisition, Methodology, Project administration, Resources, Supervision, Writing original draft, Writing review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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