Disability effects on daily activity type and duration

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Abstract. Equity concerns of urban planners and policy-makers cannot be addressed unless disability effects on daily activities are disentangled. The findings, however, strongly depend on how disability is incorporated into the model. Two Multiple Discrete-Continuous Extreme Value (MDCEV) models for analyzing disability effects on daily activity type and duration are discussed and compared in this paper. In the “classic” approach, an independent dummy variable is used to distinguish disability. However, in the “separate” approach, the dataset is divided into disabled and non-disabled groups and, then, a separate model is calibrated for the disabled group. The two approaches achieve different coefficients and elasticity values, evidencing that model specification matters for policy assessments. Three transferability metrics are adopted to illustrate that the separate approach outperforms the classic approach in explaining travel patterns of persons with disabilities. Finally, three policies that have been practiced across the globe to prevent social exclusion of disabled people are discussed in terms of the effects of model specification on the policy assessment outcomes. This assessment offers managerial insights for policy-makers to develop appropriate infrastructure and accessibility strategies for disabled people.

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1. Introduction

The World Bank reported that approximately 15 percent of the entire world population experienced disability in 2018 [1]. Persons with disabilities have different travel patterns as a result of their special physical conditions [2,3]. In the US, transportation difficulties keep over half a million disabled at home [4]. Other studies have also demonstrated that persons with disabilities are more likely to stay at home [5–7] and they have relatively lower trip rates [8,9] than the others. Those with disabilities are less likely to participate in recreational activities [10], have less tendency to drive [8], and are exposed to poverty [8] more than the others. These conditions reveal the limitation and exclusion that disabled population face. Hence, the United Nations compiled an international human rights treaty (the convention on the rights of persons with disabilities) to protect the rights of people with disabilities. According to this convention, policy-makers should consider the sensitivity of this vulnerable group and improve equity between various segments of society.

Studying activity and travel behavior of these segments of the population can diminish social exclusion and increase their quality of life. A handful of places in the world have conducted specific activity-travel surveys that are tailored for disabled individuals to evaluate relevant policies [11]. In fact, there is no regular travel behavior survey tailored for disabled people, primarily due to the data collection challenges. On the other hand, activity-travel surveys are regularly conducted in several cities for general transportation
planning purposes. Such data could have several by-products including travel behavior models for disabled people. Traditionally, dummy variables are used in general models to distinguish disability. However, a key step for studying disabled people’s travel behavior is to understand how the representation of disability affects the conclusions.

Activity type and duration are two critical travel demand factors that should be systematically studied to come up with policies that target social exclusion of disabled people. MDCEV (Multiple Discrete-Continuous Extreme Value) models have been increasingly used in the past decade since they outperform the conventional formulations by jointly modeling the activity type and duration [12]. Accordingly, MDCEV family models are selected to compare disability effects on daily activity type and duration in two modeling approaches. In the “classic” approach, an independent dummy variable is used to distinguish disability, whereas the dataset is divided into disabled and non-disabled groups in the “separate” approach, and a model is directly calibrated for disabled population. The hypothesis that the classic approach and the separate approach have similar findings is evaluated in this paper. It is worth mentioning that neither the classic approach nor the separate approach is automatically profitable than the other in every research question of interest [13]. Hence, various studies have applied different approaches, especially in regression models (see [14–16] for using a category-wise separate approach over classic approach and see [13, 17, 18] for using dummy variables over separate approach). However, to the best of our knowledge, no study has yet considered using dummy variables versus the separate approach in MDCEV models. Consequently, the goal of this study is to not only elicit the travel behavior of persons with disabilities but also compare the outcomes of the classic and separate approaches.

In the following, the relevant literature, a description of the data, and the applied MDCEV method are discussed. Then, the estimated MDCEV models, interpretation of the results, and comparisons between the classic and separate approaches are presented. Finally, the policy implications and the concluding remarks are elaborated.

2. Background

Travel patterns of disabled people are typically analyzed in two ways: First, general activity-travel surveys are used to estimate a model in which disability is somehow differentiated [19]. Second, specific surveys that are tailored for disabled individuals are conducted to provide detailed information on their daily activity routines [20]. Although the second class of the studies could provide valuable data and is encouraged to do so [21], a handful of cities/countries have conducted such surveys [11, 22]. In fact, there is no activity-travel survey tailored for disabled people that is routinely conducted, primarily due to the data collection challenges [23].

Among the first group, several studies [19, 24, 25] use dummy variables to distinguish disability, while other studies develop separate models for persons with disabilities by extracting disabled people observations from the regular travel data [26, 27]. The results of the studies in which disability is differentiated by dummy variables indicate that disabled individuals have relatively few tendencies to participate in out-of-home activities such as leisure [24] and shopping [28] because of their mobility limitations. Among the separate models are Stern [26] who introduced a Poisson model to explain the activity purpose and Schmöcker et al. [27] who used an ordered Probit model to analyze different activity purposes. Stern [26] argued that walking problems declined out-of-home activity participation, except for medical purposes; Schmöcker et al. [27] also found that walking difficulties did not affect work trips. However, researchers [29] found that individuals with disabilities had impacts on crowd walking speed and mutually walking facilities had considerable impacts on the mobility of disabled people.

Among the second group of studies, on the other hand, is a study by Páez and Farber [20] who illustrated the impact of type and severity of disability on leisure activities for adults by using the 2006 Participation and Activity Limitation Survey (PALS). In another study, Ravulaparthi et al. [30] showed that disabled people who engaged in out-of-home activities reported higher levels of subjective well-being leading to a better quality of life based on data from the Disability and Use of Time (DUST), 2009.

Table 1 summarizes a selection of studies focused on activity type and/or time-use modeling for persons with disabilities. As shown in this table, very few studies have focused on activity type and duration modeling jointly. Among the joint models, no research has been specifically designed for persons with disabilities. Only in a few studies, disability status is considered as a 0/1 explanatory variable to recognize how the disability affects activity patterns.

The following shortcomings recorded in the literature are identified and focused on in this study:

1. Travel behavior of disabled individuals has a rich literature, but there are very few studies that consider the interdependency of their activity type and duration;
2. Typical activity-travel surveys are occasionally adopted to explain travel behavior in general and differentiate disability with 0/1 variables;
3. The coefficients of many variables are assumed
similar among disabled people and others, except for very few variables that are differentiated with dummy variables.

Despite some limitations in this study, we attempt to address the aforementioned shortcomings.

3. Data

The data collected in the Household Travel Survey by the Atlanta Regional Commission were used in this study because:

1. The paper aimed at analyzing the traditional activity-travel data differently and provided a better explanation for travel behavior of disabled people;
2. The data is available for free and the results could be reproduced and verified.

In this survey, one-day activity and travel information were collected from 10,278 households including 25,810 persons with 93,713 trips in 2011 [31]. Around 5.2 percent of the sample was identified as persons with disabilities including limited mobility (37.2 percent), mental disabilities (10.4 percent), visual impairment (8.9 percent), and hearing impairment (1.4 percent).

Twenty-five activity purposes were defined in the original data [32]. In this study, activities are aggregated and classified into 6 groups: (1) in-home (H), (2) work/school (W), (3) healthcare (HC), (4) shopping (SH), (5) recreational (R), and (6) other (O) activities. All the households reported 119,480 activities, among which disabled people conducted 4,363 (3.65 percent). The numbers of people that reported each activity along with the average duration of each activity are presented in Table 2. It can be observed that the average time that persons with disabilities spend on in-home activities is about 1.25 times higher than all the people. Also, the average time that persons with disabilities
allocate to healthcare activities is more than twice of all the people. The portion of persons with disabilities who participated in work/school activities is about five times less than all the people. Also, Table 3 provides a description and definition of household and individual socio-demographic variables used in this study.

4. Method and model

Joint models are increasingly used for activity and travel-related decisions since several studies have found that joint formulations outperform the conventional ones where decisions are interdependent [33–36]. Particularly, several studies [37, 38] have argued the benefits of joint model specifications for activity type and duration models. Thus, MDCEV formulation [39] that allows modeling the choice of multiple activity types while accounting for the duration of each activity over a day is adopted in this study. MDCEV models are widely used in transportation-related studies including carsharing vehicle choice and usage [40], household vehicle ownership [41, 42], transportation expenditures [43], and energy consumption [44]. Bhut [45] formulated the utility function for an individual as in Eq. (1) for K different activities, where, $\alpha_k$ and $\gamma_k$ are satisfaction and translation parameters associated with activity $k$, respectively, $x_k$ is the corresponding consumption quantity of activity $k$ ($x_k \leq 0$ for all $k$), $\beta_k$ is the coefficient vector related to activity $k$, $z_k$ is the vector of attributes for activity $k$, and $\epsilon_k$ is the unobserved characteristics of activity $k$ that impacts the baseline utility.

$$U(x) = \frac{1}{\alpha_1} \exp(\epsilon_1) \cdot (x_1)^{\alpha_1} + \sum_{k=2}^{K} \frac{\gamma_k}{\alpha_k} \left[ \frac{x_k}{\gamma_k} + 1 \right]^{\alpha_k - 1} \epsilon_k$$

$$\alpha_k \leq 1 \quad \text{and} \quad \gamma_k > 0 \quad \text{for all} \quad k.$$  

Each person maximizes his/her utility given a time budget formulated as $\sum_{k=1}^{K} x_k = E$, where $E$ is the total available time and $\epsilon_k$ is the expenditure on activity $k$ (note that $\epsilon_k = p_k \cdot x_k$ and $p_k$ is the unit price of activity $k$, which is set to 1 in this study). To determine the optimal time allocated to each activity type, the Lagrangian function is formed and the Kuhn-Tucker conditions are applied. If an “outside good” (such as in-home activity which is selected by everyone) exists, the utility function is formed as follows [45], assuming that the first activity is the outside good:

$$U(x) = \frac{1}{\alpha_1} \exp(\epsilon_1) \cdot (x_1)^{\alpha_1} + \sum_{k=2}^{K} \frac{\gamma_k}{\alpha_k} \left[ \exp(\beta_k^T z_k + \epsilon_k) \right] \left[ \frac{x_k}{\gamma_k} + 1 \right]^{\alpha_k - 1} \epsilon_k.$$  

Bhat [45] argued that $\alpha_k$ and $\gamma_k$ were empirically difficult to identify since both of them capture saturation effects. Hence, the utility function would be replaced with the following three forms:

$$U(x) = \frac{1}{\alpha_1} \exp(\epsilon_1) \cdot (x_1)^{\alpha_1} + \sum_{k=2}^{K} \frac{1}{\alpha_k} \left[ \exp(\beta_k^T z_k + \epsilon_k) \right] \left[ \frac{x_k}{\gamma_k} + 1 \right]^{\alpha_k - 1} \epsilon_k.$$  

(3-1)

$$U(x) = \frac{1}{\alpha_1} \exp(\epsilon_1) \cdot (x_1)^{\alpha_1} + \sum_{k=2}^{K} \gamma_k \left[ \exp(\beta_k^T z_k + \epsilon_k) \right] \left[ \frac{x_k}{\gamma_k} + 1 \right]^{\alpha_k - 1} \epsilon_k.$$  

(3-2)

$$U(x) = \frac{1}{\alpha_1} \exp(\epsilon_1) \cdot (x_1)^{\alpha_1} + \sum_{k=2}^{K} \frac{\gamma_k}{\alpha_k} \left[ \exp(\beta_k^T z_k + \epsilon_k) \right] \left[ \frac{x_k}{\gamma_k} + 1 \right]^{\alpha_k - 1} \epsilon_k.$$  

(3-3)
| Variable | Definition                                                                 | Disabled | Non-disabled | Whole sample |
|----------|---------------------------------------------------------------------------|----------|--------------|--------------|
| URBAN    | Being urban residential: 1, otherwise: 0                                  | 0.03     | 0.03         | 0.03         |
| DIS-URBN | A person with disability living in urban area: 1, otherwise: 0.           | -        | -            | 0.001        |
| RENT     | Having rented house: 1, otherwise: 0                                      | 0.36     | 0.13         | 0.14         |
| HHSIZ    | Household size                                                            | 2.60     | 3.23         | 3.20         |
| DHHVEH   | Having vehicle(s) in household: 1, otherwise: 0                           | 0.83     | 0.98         | 0.97         |
| LOWINC   | Household income, less than $30,000: 1, otherwise: 0                      | 0.35     | 0.07         | 0.09         |
| HHCHD    | Number of children in household                                           | 1.70     | 1.06         | 1.10         |
| LIFESTYLE| 2+ adults, at least one retired, no children: 1, otherwise: 0             | 0.35     | 0.13         | 0.14         |
| DISBLTY  | person with disability: 1, otherwise: 0                                   | -        | -            | 0.05         |
| MALE     | Gender: 1: male, 0: female                                                 | 0.40     | 0.47         | 0.47         |
| AGE      | Age of a person                                                           | 55.87    | 38.95        | 30.83        |
| DISB-AGE | Interaction of age and disability.                                        | -        | -            | 2.91         |
| LICENSE  | Having driving license: 1, otherwise: 0                                   | 0.63     | 0.95         | 0.93         |
| WALK     | Having difficulty walking: 1, otherwise: 0                                | 0.37     | -            | 0.02         |
| EMPLOY   | Employed: 1, otherwise: 0                                                 | 0.10     | 0.64         | 0.61         |
Table 3. Description of explanatory variables used in models (continued).

| Variable     | Definition                                                                 | Disabled Mean | Disabled SE | Non-disabled Mean | Non-disabled SE | Whole sample Mean | Whole sample SE |
|--------------|----------------------------------------------------------------------------|---------------|-------------|-------------------|-----------------|-------------------|-----------------|
| WORKER       | Worker: 1, otherwise: 0.                                                   | 0.13          | 0.34        | 0.69              | 0.46            | 0.65              | 0.48            |
| DISB-WRK     | A person with disability who works: 1, otherwise: 0.                       | -             | -           | -                 | -               | 0.01              | 0.09            |
| HIDEU        | Having undergraduate /graduate degree: 1, otherwise: 0.                   | 0.19          | 0.39        | 0.40              | 0.49            | 0.39              | 0.49            |
| STUDNT       | Being student: 1, otherwise: 0.                                           | 0.08          | 0.27        | 0.28              | 0.45            | 0.27              | 0.44            |
| DIS-STUD     | A person with disability who is a student: 1, otherwise: 0.               | -             | -           | -                 | -               | 0.004             | 0.06            |
| EVERYDAY     | Using public transit, nearly every day: 1, otherwise: 0.                  | 0.06          | 0.23        | 0.03              | 0.18            | 0.03              | 0.18            |
| MONTH        | Using public transit, once or twice a month: 1, otherwise: 0.             | 0.07          | 0.26        | 0.07              | 0.25            | 0.07              | 0.25            |
| DIS-MONTH    | A person with disability who uses public transit once or twice a month: 1, otherwise: 0. | - | - | - | - | 0.005 | 0.07 |
| NTRIPS       | Number of person’s trips in a day.                                        | 2.32          | 2.72        | 3.75              | 2.78            | 3.68              | 2.79            |

The probability of the expenditure of the first $M$ out of $K$ activities (with the outside good at first) is shown in Eq. (4) [45]:

$$P(x_1^*, x_2^*, x_3^*, ..., x_M^*, 0, 0, ..., 0) = \frac{1}{\sigma^{M-1}} \left[ \prod_{i=1}^{M} c_i \right] \left[ \sum_{i=1}^{M} \frac{p_i}{c_i} \right] \left[ \frac{\prod_{i=1}^{M} e^{V_i/\sigma}}{(\sum_{k=1}^{K} e^{V_{ik}/\sigma})^M} \right]$$

$$(M - 1)!,$$  

where $\sigma$ is the scale parameter set to 1 for convenience [45], $V_i$ is related to Kuhn-Tucker conditions estimated by Eq. (5) according to the selected form of the three utility functions; and $c_i = \frac{1}{\alpha_i x_i^{\gamma_i + \beta_i}}$:

$$V_k = \beta_k z_k - \ln \left( \frac{x_k}{\gamma_k} + 1 \right) - \ln(p_k)$$

$k \geq 2, \quad V_1 = (\alpha_1 - 1) \ln(x_1^*)$.  

(5-1)

$$V_k = \beta_k z_k + (\alpha_k - 1) \ln \left( \frac{x_k}{\gamma_k} + 1 \right) - \ln(p_k)$$

$k \geq 2, \quad V_1 = (\alpha_1 - 1) \ln(x_1^*)$.  

(5-2)

$$V_k = \beta_k z_k + (\alpha_k - 1) \ln \left( \frac{x_k}{\gamma_k} + 1 \right) - \ln(p_k)$$

$k \geq 2, \quad V_1 = (\alpha_1 - 1) \ln(x_1^*)$.  

(5-3)

Regarding these constraints, Bhat introduced five specifications [46] to estimate the MDCEV model while accounting for estimation of, at last, one parameter between $\alpha$ and $\gamma$. Recently, this limitation was addressed by Shamshiripour and Samimi [47] that would make the simultaneous estimation of both parameters readily possible. However, in this study, the five traditional specifications (as shown in Table 4) are adopted for all the observations in which disability is differentiated with a 0/1 variable (the classic approach). Then, all specifications are again calibrated only for the observations with disabilities (the separate
Table 4. Multi Discrete-Continuous Extreme Value (MDCEV) Specifications with outside good.

| Specification | $\alpha$ for outside good | $\alpha$ for other goods | $\gamma$ for outside good | $\gamma$ for other goods |
|---------------|---------------------------|---------------------------|---------------------------|---------------------------|
| 1             | is estimated              | is estimated              | -                         | is fixed to 1             |
| 2             | is fixed to 0             | is fixed to 0             | -                         | is estimated              |
| 3             | All are constrained to be equal and estimated | -                         | is estimated              |
| 4             | is estimated              | is fixed to 0             | -                         | is estimated              |
| 5             | is fixed to 0             | is fixed to 0             | -                         | is fixed to 1             |

*There is no gamma for outside good because it is always used.

Table 5. Results of different specifications.

| Approach       | Criteria                  | Specifications |
|----------------|---------------------------|----------------|
|                |                           | 1   | 2   | 3   | 4   | 5   |
| Classic approach | Log likelihood value     | $-230,300$ | $-216,851$ | $-216,851$ | $-216,851$ | $-273,928$ |
| BIC            |                           | 461,195     | 434,286     | 434,296     | 434,296     | 548,392     |
| Likelihood ratio test | (specification 5 is the base) | 872.56       | 114,155      | 114,155      | 114,155      | 0          |
| Number of parameters |                       | 61           | 60            | 61            | 61            | 55         |
| Separate approach | Log likelihood value     | $-9,029$     | $-8,459$     | $-8,459$     | $-8,459$     | $-107,04$   |
| BIC            |                           | 18,418       | 17,271       | 17,278       | 17,278       | 21,725      |
| Likelihood ratio test | (specification 5  | 3,349       | 4,489        | 4,489        | 4,489        | 0          |
| Number of parameters |                       | 51           | 50            | 51            | 51            | 45         |

5. Results

The best specification of each approach was selected through the log-likelihood values, likelihood values, likelihood ratio test (with the likelihood of the 5th specification, where $\alpha$ and $\gamma$ are set to zero, serves as the benchmark), and Bayesian Information Criterion (BIC) index. As shown in Table 5, the 2nd specification, where $\alpha$ is fixed to zero for all activities and $\gamma$ is estimated, outperforms the other specifications in both approaches, since it has a higher likelihood value than the 1st and 5th specifications and also a lower BIC index than the 3rd and 4th specifications. The results of this specification for the classic and separate models are discussed in the following section.

The results of classic and separate approaches are compared to investigate the potential advantages of the separate approach over the classic approach. Accordingly, the difference in coefficients and elasticity values along with three conventional transferability tests are discussed. Finally, the separate approach results are interpreted.

5.1. Comparison of the models

The results of the classic and separate approaches are presented in Tables 6 and 7. To evaluate the difference between these two approaches, the statistical significance and p-value of differences between the comparable coefficients of the classic and separate approaches are presented in Table 8. Most of the coefficients are statistically different at a level of 90 percent. For instance, the difference between AG coefficients in the healthcare activity (HC) of the classic and the separate approaches is 0.027 with a standard error of 0.01, which shows statistical significance at a level of 90 percent. As shown in Table 8, many coefficients including NTRIPS, STUDNT, HICHD, and URBAN are statistically different, while some variables such as MALE, LICENSE, and HIEDU have similar coefficients.

The differences in elasticity values are reported in Table 9 to illustrate how the changes in model coefficients could lead to different policy assessments. The elasticity is calculated by the percentage of change in allocated time to an activity after increasing a continuous independent variable by one percent, increasing a count variable by one unit, or changing a dummy variable from 0 to 1. The latter is called pseudo-elasticity.
Table 6. The Multi Discrete-Continuous Extreme Value (MDCEV) model results: baseline parameter estimates.

| Variable type | Variable name | Separate approach | Classic approach |
|---------------|---------------|-------------------|------------------|
| | W | HC | SH | R | O | W | HC | SH | R | O |
| Household socio-demographics | URBAN | - | - | - | - | -1.415 (−2.21) | - | - | - | 0.010 (0.12) | - | - |
| | DISURBN | - | - | - | - | - | - | - | - | - | -1.352 (2.22) | - | - |
| | RENT | - | - | - | - | -0.246 (−0.43) | -0.244 (−0.43) | -0.244 (−0.43) | -0.203 (−0.43) | - | - |
| | RHIIE | 0.219 (1.55) | - | - | - | -0.014 (−0.65) | -0.014 (−0.65) | -0.014 (−0.65) | -0.014 (−0.65) | - | - |
| | LOWINC | - | - | - | - | 0.027 (0.33) | -0.233 (−1.85) | -0.233 (−1.85) | -0.233 (−1.85) | -0.194 (−1.61) | 0.011 (0.12) | - |
| | HICHD | -0.342 (−1.75) | - | - | - | -0.610 (−1.49) | -0.610 (−1.49) | -0.610 (−1.49) | -0.610 (−1.49) | - | - |
| | LIFESTYLE | -0.518 (−1.52) | 0.465 (2.05) | - | - | -0.404 (−2.28) | 0.130 (1.72) | - | - | - | - |
| Individual socio-demographic | DISBLTY | - | - | - | - | -2.384 (−4.01) | 1.834 (5.08) | -0.165 (−2.00) | -0.241 (−2.98) | -0.208 (−3.82) | - |
| | MALE | - | - | - | - | -0.053 (−2.86) | -0.447 (−2.99) | - | - | -0.224 (−3.03) | -0.220 (−3.06) | - |
| | AGE | -0.031 (−0.00) | -0.007 (−0.02) | - | - | -0.011 (−0.31) | -0.016 (−0.44) | - | - | -0.020 (0.12) | -0.098 (0.70) | - |
| | DISBACE | - | - | - | - | - | - | - | - | -0.099 (−0.40) | - |
| | LICENSE | 0.032 (0.11) | - | - | - | 0.410 (2.43) | -0.410 (−4.70) | - | - | - | 0.391 (4.73) | - |
| | WALK | - | -0.285 (1.74) | - | - | 0.111 (1.77) | 0.111 (1.77) | - | - | - | - |
| | EMPLY | - | - | - | - | -0.088 (−0.39) | -0.088 (−0.39) | -0.088 (−0.39) | -0.088 (−0.39) | -0.088 (−0.39) | -0.088 (−0.39) | - |
| | WORKER | 3.051 (12.18) | -0.769 (−2.51) | - | - | 1.276 (4.50) | -0.436 (−0.67) | - | - | -0.143 (4.94) | 0.048 (1.03) | - |
| | DISB-WRK | - | - | - | - | 2.370 (54.07) | - | - | - | - |
| | RHEDU | 3.341 (8.40) | - | - | - | -0.859 (−1.24) | 0.859 (1.24) | - | - | -0.235 (−0.40) | - |
| | STUDNT | 1.821 (0.45) | - | - | - | 0.390 (2.14) | 0.390 (2.14) | - | - | 0.390 (2.14) | - |
| | DISSTUD | - | - | - | - | 2.780 (8.45) | - | - | - | - |
| | EVERYDAY | 0.052 (1.71) | - | - | - | 0.151 (0.62) | 0.151 (0.62) | - | - | 0.151 (0.62) | - |
| | MONTH | - | -0.434 (1.69) | - | - | -0.485 (−3.22) | 0.485 (3.22) | - | - | 0.485 (3.22) | - |
| | DISMONTH | - | - | - | - | 0.170 (1.01) | - | - | - | 0.170 (1.01) | - |
| | NTRIPS | - | - | - | - | -0.204 (−0.45) | 0.204 (0.45) | - | - | 0.204 (0.45) | - |

* The value provided in parentheses is t-stat.

Table 7. The Multi Discrete-Continuous Extreme Value (MDCEV) model results: baseline preference constants, translation parameters, and model properties.

| Variable type | Variable name | Separate approach | Classic approach |
|---------------|---------------|-------------------|------------------|
| | W | HC | SH | R | O | W | HC | SH | R | O |
| Baseline preference constants | Constant | -30.70 (−10.91) | -25.57 (−10.05) | -25.57 (−10.05) | -25.57 (−10.05) | -0.014 (−0.01) | -0.014 (−0.01) | -0.014 (−0.01) | -0.014 (−0.01) | - |
| Translation | γ | - | - | - | - | 6.858 (0.86) | 6.858 (0.86) | 6.858 (0.86) | 6.858 (0.86) | - |
| Model characteristics | Log likelihood value | 50 | 1157 | - | - | 0.075 | 0.075 | 0.075 | 0.075 | - |

| Baseline preference constants | Constant | -7.83 (−6.01) | -7.83 (−6.01) | -7.83 (−6.01) | -7.83 (−6.01) | -7.83 (−6.01) | -7.83 (−6.01) | -7.83 (−6.01) | -7.83 (−6.01) | - |
| Translation | γ | - | - | - | - | 6.040 (1.01) | 6.040 (1.01) | 6.040 (1.01) | 6.040 (1.01) | - |
| Model characteristics | Log likelihood value | 50 | 1157 | - | - | 0.043 | 0.043 | 0.043 | 0.043 | - |
Table 8. Difference between model coefficients.

| Variable name | Variable type | W       | HC      | SH      | R       | O       |
|---------------|---------------|---------|---------|---------|---------|---------|
|               |               | $\beta_2 - \beta_1$ | SE | t-stat | p-value | $\beta_2 - \beta_1$ | SE | t-stat | p-value | $\beta_2 - \beta_1$ | SE | t-stat | p-value | $\beta_2 - \beta_1$ | SE | t-stat | p-value |
| URBAN         |               | -       | -       | -       | -       | -       | -       | 1.425 | 0.62 | 2.30 | 0.02 | -       | -       | -       | -       | -       | -       | -       | -       | -       | -       | -       |
| RENT          |               | -       | -       | -       | -       | -       | -       | 0.271 | 0.69 | 3.12 | 0.00 | 0.032 | 0.07 | 0.48 | 0.03 | -       | -       | -       | -       | -       | -       | -       |
| HH SIZE       |               | -       | -       | -       | -       | -       | -       | -0.173 | 0.14 | -1.23 | 0.22 | -0.115 | 0.26 | -0.46 | 0.06 | 0.203 | 0.26 | 0.79 | 0.43 | -       | -       | -       | -       | -       | -       |
| DRIVER        |               | -       | -       | -       | -       | -       | -       | -0.050 | 0.17 | -0.30 | 0.77 | -0.004 | 0.18 | -0.02 | 0.98 | -       | -       | -       | -       | -       | -       | -       |
| LOW INC       |               | -       | -       | -       | -       | -       | -       | -       | -       | -       | -       | -       | -       | -       | -       | -       | -       | -       | -       | -       | -       |
| HH CHD        | Household socio-demographics | 0.322 | 0.20 | 1.65 | 0.10 | -       | -       | -       | -0.229 | 0.12 | -1.06 | 0.05 | -       | -       | -       | -       | 0.285 | 0.09 | 3.13 | 0.00 | -       | -       | -       |
| LIFESTYLE     |               | 0.111 | 0.34 | 0.32 | 0.75 | -0.335 | 0.19 | -1.76 | 0.08 | -       | -       | -       | -       | -       | -       | -       | -       | -       | -       | -       | -       |
| MALE          | Individual socio-demographics | 0.159 | 0.18 | 0.86 | 0.39 | 0.181 | 0.15 | 1.18 | 0.24 | -       | -       | -       | -       | -       | -       | -       | -       | -       | -       | -       | -       |
| AGE           |               | 0.016 | 0.01 | 1.82 | 0.07 | 0.027 | 0.01 | 4.48 | 0.00 | -       | -       | -       | -       | -       | -       | -       | -       | -       | -       | -       | -       |
| LICENSE       |               | -0.352 | 0.29 | -1.20 | 0.23 | -       | -       | -       | -       | -       | -       | -       | -       | -       | -       | -       | -       | -       | -       | -       |
| WALK          |               | -       | -       | -       | -       | 0.002 | 0.23 | 0.01 | 0.09 | -       | -       | -       | -       | -       | -       | -       | -       | -       | -       | -       |
| EMPLOY        |               | -       | -       | -       | -       | 0.550 | 0.29 | 1.89 | 0.00 | 0.008 | 0.24 | 0.28 | 0.78 | 0.152 | 0.24 | 0.65 | 0.22 | -       | -       | -       | -       | -       |
| WORKER        |               | -2.376 | 0.41 | -5.76 | 0.00 | 0.274 | 0.29 | 0.04 | 0.35 | -       | -       | -       | -       | -       | -       | -       | -       | -       | -       | -       |
| HIEDU         |               | -       | -       | -       | -       | -       | -       | -       | -       | -       | -       | -       | -       | -       | -       | -       | -       | -       | -       | -       |
| STUDNT        |               | -2.700 | 0.40 | -6.82 | 0.00 | -       | -       | -       | -       | -       | -       | -       | -       | -       | -       | -       | -       | -       | -       | -       |
| EVERYDAY      |               | 0.051 | 0.33 | 0.16 | 0.88 | -       | -       | -       | -       | -       | -       | -       | -       | -       | -       | -       | -       | 0.578 | 0.25 | 2.30 | 0.02 | -       | -       |
| MONTH         |               | -       | -       | -       | -       | -       | -       | -       | -       | -       | -       | -       | -       | -       | -       | -       | -       | 0.264 | 0.28 | -0.95 | 0.34 | -       | -       |
| NTRIPS        |               | -       | -       | -       | -       | -       | -       | -       | -       | -       | -       | -       | -       | -       | -       | -       | -       | -       | -       | -       | -       |


Table 9: Elasticity-effects and difference between elasticities of two approaches.

| Variable Type | Variable Name | Homogeneous Sector | Individual Sector |
|---------------|---------------|--------------------|------------------|
| Urban         | Urban         | 0.00               | 0.00             |
| Rural         | Rural         | 0.00               | 0.00             |
| Energy        | Energy        | 0.00               | 0.00             |
| Agriculture   | Agriculture   | 0.00               | 0.00             |

a) Italics numbers are direct elasticity; b) Bold numbers indicate difference in sign.
which is not accurate since derivative values are reliable only in the vicinity of the observed point, but its relative magnitude of the two approaches could be informative. For predicting the time allocated to each activity with the MDCEV model, before and after changing a variable, an algorithm introduced by Pinjari and Bhat [48] is applied. The percentage of change in activity duration due to a change in a specific independent variable is also reported in Table 9. Most of the elasticities are statistically different at a level of 90 percent. For instance, having academic education has a stronger effect on reducing healthcare activities in the separate approach than the classic one (−0.62 versus −0.13). Similarly, the effect of having at least one vehicle in the household on the participation of persons with disabilities in shopping activities is 2.5 times stronger in the separate approach than the classic one.

Model transferability metrics could evaluate the ability of a transferred model in explaining the behaviors of the model for a new data set. Three conventional transferability measures namely Transferability Test Statistic (TTS), Transfer Index (TI), and the Transfer Rho-square ($\rho^2$) affirm that the separate model could not be replaced by the classic model.

Atherton and Ben-Akiva [49] defined the TTS as in Eq. (6):

$$TTS_j = -2 \left( LL_j(\theta_i) - LL_j(\theta_j) \right),$$

where $LL_j(\theta_i)$ is the log-likelihood value estimated by observed data $j$ and the transferred model coefficients $i$, and $LL_j(\theta_j)$ is the log-likelihood value estimated by observed data $j$ and the model coefficients $j$. In this case, $j$ refers to the separate model for persons with disabilities and $i$ is a representative of the classic model which includes all observations from the data set. Accordingly, the TTS value would be 492. Given that TTS follows Chi-square distribution with degrees of freedom equal to the number of parameters, the hypothesis that the classic model could be transferred to disabled people is rejected at a significance level of 95 percent.

TI, introduced by Koppelman and Wilmot [50], has an upper limit of one (i.e., the transferred model is as accurate as the local one) and is calculated by Eq. (7):

$$TI_j(\theta_i) = \frac{LL_j(\theta_i) - LL_j(C)}{LL_j(C) - LL_j(\theta_j)},$$

where $LL_j(C)$ is the log-likelihood value of the model $j$ estimated with constants only, and $LL_j(\theta_i)$ and $LL_j(\theta_j)$ have similar definitions to the TTS metric. The TI value for the classic model is computed to be 0.64. This means that the classic model ($i$) is less fit for the travel behavior of persons with disabilities than the separate model.

The transfer Rho-square ($\rho^2$) is the third transferability measure which is analogous to the commonly used Rho-squared measure [51] and is obtained by Eq. (8):

$$\rho^2_j(\theta_i) = 1 - \frac{LL_j(\theta_i)}{LL_j(C)},$$

$\rho^2$ is upper bounded by the local Rho-squared. However, in this case, its value is 0.048 which is considerably lower than that of the separate model (0.075). The threefold comparisons discussed in this section reveal that the separate approach has different coefficients and policy outcomes and outperforms the classic approach in explaining the travel patterns of persons with disabilities.

5.2. Interpretation of the results
The separate MDCEV model, as the superior model, is interpreted in this section. This includes discussions on the effects of household socio-demographics on baseline utility, effects of individual socio-demographics on baseline utility, baseline preference constants, and translation parameters.

Household socio-demographics, including lifestyle, residence area type, household income, household size, vehicle ownership, and the number of children, turned out to be statistically significant in the baseline utility. Understandably, persons with disabilities who live in urban areas spend less time on recreational activities than disabled persons who live in other areas. Disabled individuals in large families have a lower propensity to participate in shopping activities. This consequence reflects that the presence of other people for doing maintenance shopping prevents disabled individuals from shopping.

They are also less likely to spend time on recreational activities. Pinjari and Bhat (2010) [28] also came up with the same outcomes, showing that non-workers spend less time on out-of-home discretionary activities in larger families. However, by increasing the number of children, preference for shopping activities among persons with disabilities rises. In this case, if the disabled person is a parent, he/she is responsible for doing shopping and if the disabled person is a child, he/she might be accompanied by other children and parents. As a result, the probability of spending time on shopping activities increases. Further, disabled individuals are more likely to have work/school, shopping, and recreational activities in families with at least one vehicle due to the flexibility and improved access to private mode. In low-income households, disabled individuals tend to have fewer recreational activities. Bhat (2005) [39], also, argued that higher income would reinforce the ability to participate in out-of-home recreational activities. Interestingly, persons with disabilities in low-income families are more likely
to spend time on shopping activities. It is commonly believed that a person with disability in a low-income family will need some more time to find good deals for mandatory shopping, e.g., grocery than those in high-income households. Online shopping and hiring someone to do their shopping might be unattainable for disabled people in low-income families, as well. Finally, less tendency for work/school and more propensity for healthcare activities are observed in families with more than two adults, at least one retired, and no children.

Individual socio-demographics such as age, gender, education, having a driving license, and employment status have remarkable effects on the activity patterns of disabled people. Elderly persons with disabilities, for instance, are less inclined toward working. According to Table 9, work activities decline by 0.38 percent as age increases by 1 percent. Males with disabilities are less likely to have shopping or healthcare activities than disabled females. This is in line with the findings of Pinjari and Bhat (2010) [28]. Further, persons with disabilities who rarely use public transport spend much time on healthcare activities and participate less in recreational activities. These results could be arguably attributed to their mobility limitations. In contrast, disabled people who often use public transport are more likely to participate in work activities. This might be due to either better physical condition of the disabled person or better access to adjusted public transport. Among disability types, walking difficulty results in more participation in healthcare activities. However, there is no significant effect found for other types of disability, possibly due to their limited observations in the data. On the contrary, persons with disabilities who work are less inclined to spend time on healthcare activities. Indeed, being a worker/employment has an adverse effect on participating in all activity types except for work/school. This result is consistent with what Pinjari et al. (2009) [25] concluded. Furthermore, people with disabilities with an academic degree participate more in recreational activities.

The baseline preference constants are representatives of the general preference for each activity type relative to the base category (i.e., in-home activity). In this study, all the baseline preference constants are negative, meaning that in-home activity is most preferred and all individuals participate in it. Also, at a point when no time has yet been spent in any activity type, the least preferred activity purpose among persons with disabilities is recreation because it has the lowest value among baseline preference constants.

The translation parameters (γ_k) for all activity types (except for in-home as the outside good) and the corresponding t-stats are provided in Table 7. The magnitude of the parameter γ_k is inversely related to the satiation effect for activity purpose k. Therefore, a value of γ closer to zero results in higher satiation and, consequently, the lower time consumed in activity type k. The results indicate that the shortest activity duration among persons with disabilities is shopping, meaning that this activity has the highest satiation effects. On the other hand, the lowest satiation effect belongs to work/school activities that is understandable for mandatory activities.

6. Policy implication

An essential application of travel pattern models for disabled people is to evaluate potential policies that could prevent their social exclusion. Policy-sensitive variables in the proposed models include income, residential area type, having a driving license, employment status, level of education, and public transport usage. Among these, vehicle ownership, public transport usage, and education are of particular interest since the classic and the separate approaches provide different policy outcomes. These are discussed in more detail in this section.

Improving access to auto vehicles could patronize disabled individuals to participate in out-of-home activities. Recently, theoretical studies have also analyzed the effect of using a private automated vehicle that significantly improves the accessibility for persons with disabilities [52, 53]. Thus, policymakers who wish to encourage persons with disabilities to participate in such activities should find methods to think about relevant vehicle ownership policies. Queensland authorities in Australia, for instance, offer special subsidies so that disabled people could purchase or modify a car for their special needs through the vehicle options subsidy scheme [54]. To justify the budget for such programs, policy-makers need to be aware of the impacts on travel-activity patterns of the disabled. The preferred model specification could strongly affect policy assessment outcomes. As shown in Table 9, for example, shopping and recreational activities drastically increase, if a household has access to a private automobile. However, the magnitude of this change is 2 and 2.5 times higher for recreational and shopping activities, respectively, in the separate approach than the classic approach. Thus, the benefits of this program in terms of promoting shopping and recreational activities would be underestimated if the classic approach is adopted instead of the separate approach. Similar arguments could be made for other variables, as well.

Promoting public transport use for disabled people is a concern among many city officials since several studies proved that persons with disabilities have much higher reliance on public transportation to make trips [55, 56] and barriers of public transportation stop people with disabilities to participate in society [57]. The
West Virginia Country Roads Transit (CART) modified buses and vans with wheelchair lifts or ramps to meet the needs of persons with disabilities who use public transportation. Operators are trained to assist persons with disabilities, secure wheelchairs, provide information on destinations, and announce stops [58]. Training programs for persons with disabilities can also improve the overall skills needed for using public transportation [59]. Similarly, model specification plays a key role in ensuring the success of policy assessments. As shown in Table 9, those who regularly use public transport are less likely to have healthcare activities. However, the effect of using public transport on healthcare activity participation is 5 times higher in the classic approach than the separate one. There are opposite signs in elasticity results in some cases. For instance, Table 9 illustrates that if all persons with disabilities use public transportation rarely, their participation in recreational activities will reduce by 11.9 percent. However, under this circumstance, the classic approach surprisingly shows a 92.4 percent increase in recreational activities.

Facilitating higher education for disabled people is another policy to prevent social exclusion. Some countries ratified the 1990 UNESCO’s Convention Against Discrimination in Education (CADE) in support of providing better education for disabled people. Some actions are taken in different countries to give persons with disabilities a greater chance of education such as allocating the grant to students with permanent disabilities in Canada [60]. Likewise, the University of Iowa offers door-to-door transit services for students with disabilities called CAMBUS [61]. Again, such policies need to be justified based on facts and figures. As demonstrated in Table 9, if all persons with disabilities have an undergraduate/graduate degree, healthcare activities drop 4.8 times more in the separate approach than in the classic approach (0.62 versus 0.13). Therefore, making decisions based on the separate model for persons with disabilities would result in different policy evaluations.

7. Conclusion

Household travel surveys showed that individuals with disabilities participated in fewer out-of-home activities. Hence, they are at a higher risk of depression, poverty, and other socio-economic damages. A better picture of their travel behavior might enable the decision-makers to help them engage in various out-of-home activities. This study is an attempt to explore the impact of the way that disability is modeled on the policy assessment outcomes. For this purpose, two Multi Discrete-Continuous Extreme Value (MDCEV) models were developed to jointly model the activity type and duration. The first MDCEV model (classic approach) reflected disability as a dummy variable and its interactions with some other variables such as age and employment. The second MDCEV model (separate approach) was estimated only for persons with disabilities. Comparing these two approaches indicated that the way that disability was modeled could affect the results. Statistically significant changes in most coefficients and elasticity values were found. Further, three model transferability metrics (i.e., transferability test statistic, transfer index, and the transfer rho-square) affirm that the separate approach outperformed the classic approach.

Policy assessments should be carried out according to mathematical models that picture the relevant outcomes. Policies that aim at promoting the social involvement of disabled people incur certain costs for the governments that need to be justified. In the absence of routine activity-travel surveys for the disabled community, assessments could be done at almost zero costs by the typical activity-travel surveys that are regularly carried out for general transportation planning purposes. Adapting an improper functional form, however, may result in over/underestimation of the policy outcomes.

This study is an attempt to show that the customary activity-travel surveys and the existing data banks can be used to fine-tune outputs for persons with disabilities by applying appropriate methods. Although the effects of some important variables such as type and severity of disability on activity participation are tangible, it is not possible for every city to collect special data for persons with disabilities. Even though differentiating weekdays and seasons could understandably improve the models, we were bound to the data limitations. Similarly, we lacked land-use variables. Hence, investigating the effect of such variables on activity participation needs to be addressed in future studies. Besides, the way that disability affects the decisions of family members can be considered using the concept of group decision-making, which models the interactions between the group members.

Data availability

All data used during the study is available on the Metropolitan Travel Survey Archive website (http://www.surveyarchive.org/) for free, and the code of the MDCEV model used in this study is also available in Chandra Bhat’s profile as public codes (http://www.caee.utexas.edu/prof/bhat/MDCEV.html).

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Biographies

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