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How do transfer penalties impact travel time savings?

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Ridesourcing for the first/last mile: How do transfer penalties impact travel time savings?

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Problem statement

The first and last mile of public transportation (PT) trips are a long known problem to planners: low and dispersed spacio-temporal demand is expensive to serve with large-capacity vehicles, yet they deter many potential passengers from using PT. Demand-responsive feeders have been suggested as a remedy (see Chandra and Quadrioglio, 2013, for an overview) in three phases:

In the 20th century ('phase 1'), demand-responsive transportation generally faced technological constraints (manual routing, scheduling and dispatching, corresponding high labor costs, long lead times), resulting in low levels of ridership and/or high expenditures (Mageean and Nelson, 2003; Davison et al., 2014).

The dissemination of GPS-enabled smartphones, advances in routing algorithms and computing power, and regulatory voids have enabled new (cost-)efficiencies in demand-responsive transportation and led to the popularity of ridesourcing companies such as Uber or Lyft ('phase 2'). Their use as first/last mile feeders has often been suggested (e.g., Feigon and Murphy, 2016; Westervelt et al., 2017; Shaheen and Chan, 2018) and many US transit agencies have engaged in partnerships to subsidize first/last mile rides (e.g., Charlotte, Austin, Centennial, Pinellas County) or are planning to do so (e.g., Los Angeles, Chicago). Ridership, however, has so-far been low and operations of ridesourcing companies remain deficient.

Perhaps most importantly, the first and last mile is seen as one area of application where automated taxis could complement PT ('phase 3') (Chong et al., 2011; Liang et al., 2016; Cervero, 2017; Moorthy et al., 2017; Shen et al., 2018). While profitable operations can be expected (Loeb and Kockelman, 2017; Boesch et al., 2018), it is unclear whether ridership on the first/last mile will finally meet expectations or whether a conceptual barrier to demand-responsive feeders for the first/last mile persists.

Literature review

So-far, mostly *operational* explanations for low ridership of first/last mile ridesourcing services have been identified (e.g., sparse marketing, short pilot duration, small pilot area, high costs) (City of Centennial, 2017; PSTA, 2018).

Despite a long history of research into transfers and associated disutilities ('transfer penalty') (Algers et al., 1975; Alter, 1976; Allen and DiCesare, 1976; Newell, 1979; Horowitz, 1981), the additional transfers caused by first/last mile demand-responsive feeders have not

55 been considered as a *conceptual barrier* to their use. Yet, this seems important as
56 passengers prefer to avoid additional transfers due to factors such as anxiety to reach the
57 subsequent connection, security, activity disruption and comfort (Currie, 2005; Iseki and
58 Taylor, 2009; Cheng, 2010).

59 Studies investigating the general size of the transfer penalty exhibit wide value
60 ranges. Currie (2005) provides a review finding an average transfer penalty for bus-bus
61 transfers of 22 min of in-vehicle travel time (ranging between 5 and 50 minutes). Reasons
62 for these wide ranges are context-sensitivity (e.g., climate, security, local amenities, type of
63 vehicle) (Iseki and Taylor, 2010; Guo and Wilson, 2011) and measurement scope (e.g.,
64 waiting time, walking time to the subsequent vehicle, and/or the disutility of the transfer itself)
65 (Garcia-Martinez *et al.*, 2018). In a recent effort to improve comparability, Garcia-Martinez *et al.*
66 (2018) investigate the 'pure transfer penalty' (i.e., without walking or waiting times). Using
67 SP data in Madrid, they find the pure transfer penalty to average 15.2 min.

68 Yan *et al.* (2018) are the first to consider a transfer penalty in their survey-based
69 investigation of traveler responses to a potential first/last mile ridesourcing service on the
70 University of Michigan Ann Arbor campus. Despite finding a transfer penalty of 10.9 min in-
71 vehicle travel time, they conclude: "when used to provide convenient last-mile connections,
72 ridesourcing could provide a significant boost to transit". (p. 1)

73

74 **Research objectives**

75

76 Complementing popular *operational* explanations, we argue that the additional transfer and
77 associated penalty provide a *conceptual* explanation for low ridership of current first/last mile
78 ridesourcing services as well as future first/last mile usage of automated taxis. In this study,
79 we aim to quantify the relative impact of transfer penalties on the total time travel time
80 savings using first/last mile demand-responsive feeders empirically.

81

82 **Methodological approach**

83

84 As a case study, we chose Pinellas County, Florida, which is home to the longest operating
85 first/last mile ridesourcing partnership ('PSTA Direct Connect'). We obtain block-group level
86 origin-destination commuting trip information from the 2015 US Census Origin-Destination
87 Employment Statistics (99 470 observations). For each, we construct PT travel times
88 including access/egress walking times and intermediate wait times using the Google
89 Directions API (Alternative A). We then obtain the coordinates of the first and last PT station
90 used and, using the Google Directions API, construct first/last mile car trips from the origin to
91 the first PT station used, and from the last PT station to the destination (Alternative B). We

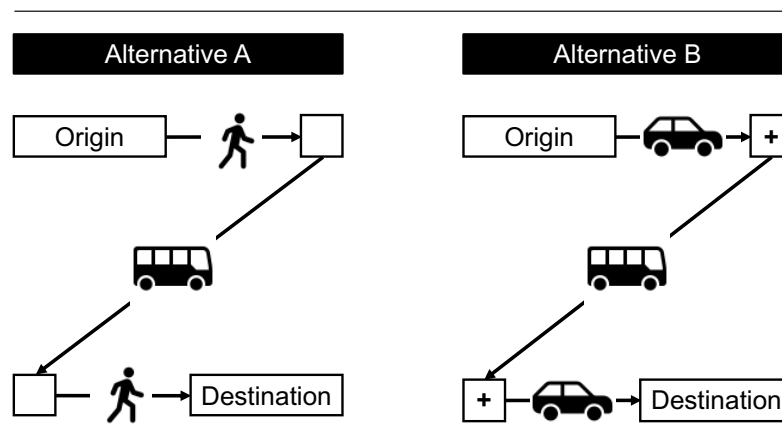


Fig. 1: Alternatives without (A) and with (B) first/last mile DRF, for which travel times are being compared. Transfer penalties are added to Alternative B.

92 then compare weighed travel times for A and B adding a transfer penalty between 5 and 15
93 minutes for the first/last mile transfer (Figure 1).

94

95 Results

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97 We find that a first/last mile service leads to average travel time savings of 15.7 minutes.
98 However, transfer penalties of 5, 10 and 15 minutes diminish travel time savings by 54%,
99 82% and 95%, respectively (Figure 2). Thus, even at small values the transfer penalty
100 presents an important conceptual barrier to first/last mile demand-responsive feeders.
101

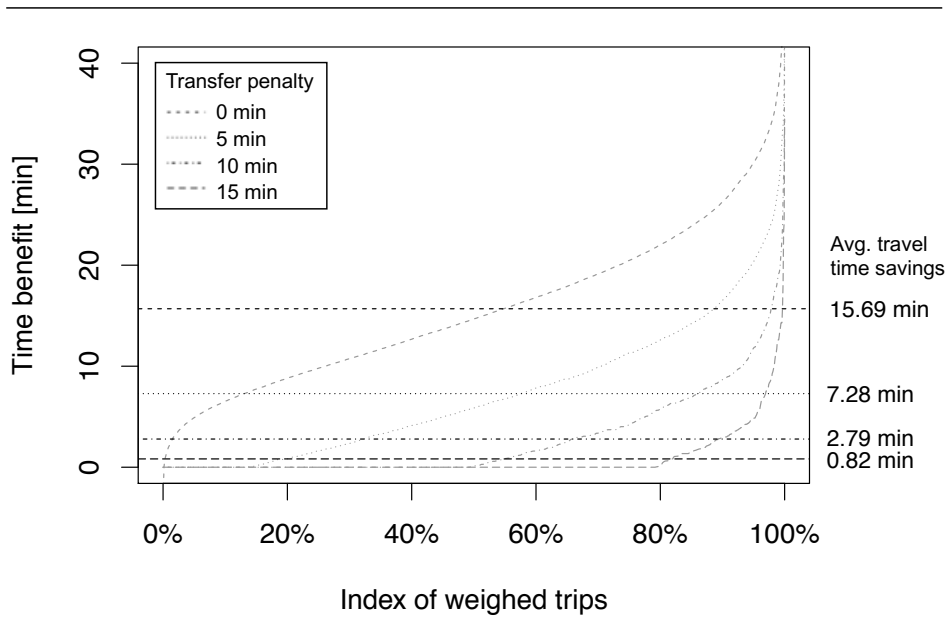


Fig. 2: Travel time savings for first/last mile trips after applying transfer penalties.

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103 Discussion

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105 Our results not only help to explain the low ridership of current first/last mile ridesourcing
106 services, they also help to explain why a significant and substantive positive relationship
107 between ridesourcing and public transit ridership for urban areas has not been found yet.
108 Furthermore, they conceptually question the usefulness of demand-responsive feeders on
109 the first/last mile, including automated taxis.

110 Future work investigating ridesourcing or automated taxis as potential first/last mile
111 solutions similar to Moorthy *et al.* (2017) and Shen *et al.* (2018) might come to a different
112 conclusion once considering transfer penalties. Taking into account a distribution of transfer
113 penalties, however, might be more accurate to reproduce real-world preferences than our
114 simplistic, yet illustrative approach of considering averages. As values are highly context-
115 dependent, it seems important to study local factors such as the built environment, safety
116 and weather conditions carefully to make meaningful assumptions.

117 Our results finally suggest the following policy implication. Vehicle-based first/last
118 mile services in general (including automated taxis) appear to decrease perceived travel
119 times (including the transfer penalty) only in areas with particularly long ingress/egress
120 distances. Even in suburban Pinellas County with an average population density of
121 1368/km² and an average first/last mile of 900m, distances seem too close for a first/last
122 mile demand-responsive feeder to improve perceived travel times substantially. Thus, in
123 contrast to current studies, first/last mile services appear more relevant in less urbanized /
124 rural areas or for connections to (sub)urban high-speed PT such as rail or BRT.

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126 **References**

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