Exploring How to Personalize Travel Mode Recommendations For Urban Transportation

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ABSTRACT

The diverse transportation services of today's cities pose a significant opportunity for personalizing route planning user's experiences. To understand what people are taking into account in mobility decisions, we present a pair of human studies. First, we conducted interviews to explore what factors people consider to make decisions about their travel. Then, we designed, ran, and analyzed a survey to study which of those factors are crucial to model for understanding mobility decisions and behavior. Our analysis indicates that people's mobility decisions incorporate considerably more information than current applications support. Also, differences in people's experience, personality, and requirements significantly impact their mode choice preferences. We close with a discussion about how these findings go beyond trip planning to other potential smart cities problems.

CCS CONCEPTS

• **Human-centered computing → Empirical studies in collaborative and social computing**; User centered design; • **Applied computing** → *Transportation.*

KEYWORDS

transportation, intelligent personalization, user modeling, AI assistant, travel application, personalized interfaces, smart cities, urban computing, sustainability, mobile app, commuting

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1 INTRODUCTION

The last decade has seen explosive growth in mobility offerings. Ridehail, rideshare, carshare, bikeshare and dockless scooter services all compliment the personal vehicle and existing public transit. To aggregate these offerings, companies (e.g., TripGo and Moovel) have been developing applications to enable trip planning and payment across these services. The diversity of offerings and population travel needs present a challenge for creating personalized interfaces that help people make transportation decisions. An important component of generating good recommendation is understanding a person's trip context so that a relevant mode from a set of alternatives can be suggested.

As an example, consider Jane who wants to commute to her office and uses a travel application on her phone to figure out how to get there. The travel app suggests walking to the bus stop and taking the direct bus to office - chosen from all available route alternatives. This recommended trip has been personalized to Jane's trip context. The app makes this suggestion by considering that the bus route is direct and has frequent service, the bus stop is nearby, the weather is pleasant, and that she values that she can work while traveling on the bus.

This paper studies what constitutes a person's trip context that is useful in generating recommendations as in the example above. In this paper, we approach the problem of characterizing an individual's trip context as follows:

- we leverage previous transportation research and psychological research of personality traits to generate an an initial set of factors;
- we conducted 20 traveler interviews to support the initial set of factors as well as generate new ones;
- we conducted a survey study with 235 participants from urban locations in the US to statistically validate factors generated in the previous steps.

Through this approach, we identified a significantly expanded set of trip context factors grouped into two categories below:

- Static: Factors that do not change day to day
  - Network: Factors related to the transportation local transportation options
  - Personal: Factors related to an individual's perception and experience with various transportation options
  - Personal traits: Factors related to an individual's personality
- Dynamic context: Factors related to the trips purpose, the weather, and transportation network that vary from day to day.

The rest of this paper is organized as follows. We begin by briefly summarizing prior work on understanding traveler context in Section 2. We describe our user interview methodology and results in Section 3. Then in Section 4, we present our survey and highlight factors of potential value for personalization. We close with a discussion of implications for smart cities in Section 5.

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2 RELATED WORK

Researchers from diverse backgrounds have provided partial answers to this question. Transportation mode choice research typically focuses on travel time and cost with more complex models including additional factors for income, auto ownership, and purpose [12]. These models characterize the utility of taking a specific mode for travel using a linear combination of measurable factors (e.g, travel time, travel cost, walk distance, personal income) collected through public surveys [15]. The likelihood of a traveler taking a specific mode is based on its measured utility. Meanwhile, AI route planning algorithms focus largely on time and cost [3] with a few exceptions (e.g., energy [7], number of transfers [6], reliability [2]). Others [16] have studied the association between personality and transportation decisions in urban environments. City-wide deployment of sensors and collection of personal data significantly expands the space of measurable factors enabling the opportunity for greater personalization. Our research takes a step beyond these isolated strands of research and determines a comprehensive set of factors that can be used for personalizing travel recommendations.

3 TRAVELER INTERVIEWS

Our approach to understanding a traveler's trip context begins by supplementing existing social science research [4][19] with interviews. These open-ended, semi-structured interviews serve to both ground the application of existing research in our setting and generate new hypotheses to explore.

3.1 Method

To elicit information relevant to mode choices, we developed a guide to conduct 30 minute, semi-structured interviews with participants. The guide contained probes detailing information of interest that were not be read aloud. The interview began with the participant signing an informed consent form that provided details about the overall project. The interviewer and the participant were instructed to not use the participant's name or any other identifying information about them. Then, the participants were asked to provide details about themselves, including age, gender, occupation, as well as accessibility of various transportation at their home, office, and regular shopping location. The interviewer guided participants to describe their mobility routines including the locations they regularly visited and how flexible time to reach there was. Participants were asked to provide details about their usual travel (to work, shopping, social outing, other outings), available alternatives, and circumstances under which they would consider an alternative. The interviewer probed about how the participant would change their commute if they were recommended an alternative that would help congestion. Interviewer also asked about what effortful activity a participant did because it was good for the environment. Participants described their attitudes towards public transit. Additionally, participants also discussed the information they would like to know if they were recommended an alternative. The interview ended with a general open-ended conversation about travelling in Los Angeles and an appreciation for the participant's time.

Using the guide, we interviewed 20 people (7 women, 13 men) in the age range 21-79 (mean 37.5, standard deviation 16.8) in Los Angeles. For their efforts, the participants were paid $40 using Amazon gift-cards or checks based on their preference.

3.2 Data Analysis and Results

The interviews were recorded and transcribed. One author highlighted the content which containted information about mode choice in the transcripts. In a separate meeting and through an interactive process, the authors categorized and grouped factors. Through this process, we developed a comprehensive taxonomy of factors that underlie a person's choice of mode for their commute.

3.2.1 Understanding mode choice behavior. Collectively, participants reported a variety of modes that they use for their weekly commute including private non-motorized modes - *walking* and *biking*, public transit options - *bus* and *train*, ride hailing - *Uber/Lyft/Taxi*, and shared rides - *carpools*, and private motorized modes - *driving*. Participants varied in terms of their commute with 8 people expressing a strict preference for driving regardless of where they were going. 2 people expressed a preference for working from home and driving for non-work related trips. 4 people expressed a clear preference for taking public transit, 3 for walking/biking, 2 for a ride service or carpool, and 1 for driving/biking. A few people undertook multi-modal trips that included taking a rideshare to a train station.

3.2.2 What underlies mode choice? Our analysis uncovered a large set of factors when they decided how to travel to their destination. These *mode choice* factors can be organized in a taxonomy as follows:

(1) Static factors: This grouping contains factors that do not change from trip to trip and are a property of the transportation network that a person is embedded in due to where they reside and work, to their personal situation including education and income, as well as attributes of their personality.
  (a) Network factors: Many participants corroborated the factors transportation researchers use by highlighting the cost and time trade-off they must make: P4 - *It's really time convenience and cost are the things that we would...* and *The first issue I think would be efficiency, the time of route.* Others highlighted the accessibility of public transit as an important factor: P12 - *... and since it is so close to me, my nearest transit stop, like I said, is .2 miles away, it's pretty much a no-brainer.* Participants also reported what value different modes provided to them: P12 - (about public transit) *Yeah. I do it because it's stress-free. This is Los Angeles. It is just traffic 24/7. There is no quiet time on the roads anymore...*, P13 - *While you're on the bus or on the train you can do other stuff rather than just focusing on driving. Time spent driving is basically lost time.*, P05 - *I love my car because I really enjoy listening to the radio, NPR, or music and both.*
  (b) Personal factors: Participants reported that the nature of their employment along with the flexibility it affords was a big factor in how they chose modes. P07 - *When I as working I would have taken almost any suggested mode of transportation. That would not have been an issue because I had a destination and I had an arrival destination approximate and I had a routine that could be duplicated,* P17 -

I create my own schedule so I try to always travel off peak actually.

(c) Personality: As explored previously by other researcher, our analysis showed that people's personality attributes such as *openness, commitment* etc. may affect their mode choice. Some participants expressed an openness to try new things P25 - *would be willing to try almost anything once, to be honest. That just may be my personal outlook on life* and P02 - *"When I was teaching I would sometimes drive and sometimes take the train and [I would out of conscience] try to take the train".*

(2) Dynamic context: This grouping includes factors that may change from trip-trip.

(a) Parking: P4 - *Yeah, I feel like Trader Joe's there's always that time when the parking lot's packed and you can't get a parking space and the store is sold out of stuff.*

(b) Weather: P17 - *Also, the weather here, it's super hot a lot of the time and super sunny. I don't want to be out walking around on the hot streets.*

(c) Traffic: P7 - *I would stay away from high traffic times. If I'm going to go I'm going to usually leave before four o'clock to be on my way home by five or six when traffic becomes a little more congested.*

(d) Trip purpose: P19 - *Specifically to shopping. If I were going to a mall for some reason, which I don't do particularly often, I wouldn't want to be taking a bus there just because I wouldn't want to be lugging around things that I'm buying on and off the bus.*

3.2.3 Utility of personalized travel planning. Several of the participants talked about the cognitive load of planning a trip which especially affects the decision of choosing an alternative route: P01 - *I certainly see congestion over on the Sepulveda parallel to the 405. Very, very, heavy. Puts almost an extra hour on the bus trip, but I don't really know what the solution is.*. This suggests that a travel assistant that could personalize trips to a person's context would be useful in travel planning. More importantly, participants expressed that they would be interested in different ways to make their trip if it was suggested without them having to invest time thinking: P03 - *If you were to tell me there was a different way, I would probably take it. If you were to say this is a better way to travel or more efficient way, then yeah I would be open to that.* and P19 - *So, as much information as you can take into account, I would be in favor of using that...I want as much intel as possible.*

4 TRAVEL BEHAVIOR SURVEY

The traveler interviews above uncovered a wide range of factors that underlie the decision to take a specific mode for a given trip. However, the interviewed sample only had 20 people and was limited to the Los Angeles region. In a large population, all factors may not be significant in predicting mode choice and consequently, not all factors are equally valuable personalizing travel recommendations. To determine which factors matter for a larger population sample, we designed and ran a traveler behavior survey study. We used insights from previous research and traveler interviews to generate a large set of factors that may have a role in mode choice. The study had 112 questions that measured peoples' mode choice travel behavior (via self-reports). It also recorded their mode choice context by measuring factors determined in the interview analysis and included public transportation availability and proximity, availability of other transportation modes, and evaluation of different modes as well as several dimensions of personality.

4.1 Method

We deployed the travel behavior survey via Qualtrics[1] to 677 participants from urban areas in contiguous US. The participants were recruited by a local recruiting company that were tasked to find commuters in Los Angeles county. After eliminating responses that were completed in less than a reasonable threshold time, included repetitive responses, or contained contradictory responses, we obtained 235 responses (128 women & 106 men; age 18-79, mean 46.51, sd 13.5) for further analysis. The participants were paid $20 using Amazon gift-cards or checks based on their preference. These data were analyzed as described in the following sections.

4.2 Analysis: Static Factors

We were interested in exploring how various static mode choice factors determined from previous research and traveler interviews impact mode choice behavior in our population sample. All questions were framed as multiple-choice questions.

4.2.1 Dependent variables. We define a participant's mode choice behavior as the proportion of all local trips for which they use each mode. We measured a participants mode usage via self-reports for 8 modes: walking or wheelchair, bicycle, bus or shuttle, train or subway or tram, ride services - Taxi, Uber, Lyft etc, carpools, private automobile, and motorcycle or scooter. Mode usage was measured on an ordinal scale:

1: 0-5%, 2: 5-25%, 3:25-50%, 4: 50-75%, 5: 75-95%, 6: 95-100%

Together, 8 ordinal measurements on the scale above (one for each mode) characterize a participant's mode choice behavior.

4.2.2 Independent variables. We measured participants on various types of static factors: network factors, personal factors, and personality using a variety of Likert and ordinal scales. An an example, we measured accessibility of bus by having people report:

(1) Distance from a bus stop: How long does it take to walk to the nearest bus stop/train station?
1: Don't know, 2: No local service, 3: 31-60 minutes, 4: 21-30 minutes, 5: 11-20 minutes, 6: 6-10 minutes, 7: 5 minutes or less

(2) Frequency of bus or shuttle: During rush hours, how often do public transit services depart from your nearest stop/station?
1: Don't know, 2: No local service, 3: Over an hour, 4: 31-60 minutes, 5: 21:30 minutes, 6: 11-20 minutes, 7: 6-10 minutes, 8: Every five minutes or less.

4.2.3 Multi-variate, multiple linear regression. As there are several dependent variables which together characterize mode choice behavior, we performed multi-variate, multiple linear regression analyses [8]. The regression model is of the form:

where Y is s a matrix of n observations on m dependent variables; X is a model matrix with columns for p independent variables, typically including an initial column of 1s for the regression constant; B is a matrix of regression coefficients, one column for

[1] https://www.qualtrics.com/

Table 1: Regression table showing coefficient and standard errors for each mode as a function of distance of bus/shuttle stop and frequency of bus. Values reported with independent variables are Type II MANOVA test. Significance codes for p-values: $*** < 0.001, ** < 0.01 * < 0.05, . < 0.1$.

	Private non-motorized		Public transit		Shared transit		Private motorized	
	Walking/ Wheelchair	Bicycle	Bus/shuttle	Train/ tram	Ride service	Informal carpool	Motorcycle	Private vehicle
Distance	0.08718*	0.04057	0.05233	0.06301	0.0334	-0.005703	-0.015433	-0.17464**
(0.099597 .)	(0.0386)	(-0.0278)	(-0.0358)	(-0.0364)	(-0.0221)	(-0.02953)	(-0.015)	(-0.0606)
Frequency	0.05751	0.01981	0.09132**	0.10155**	0.04659*	0.024442	0.008736	-0.16950**
(0.035358 *)	(-0.0328)	(-0.0236)	(-0.0304)	(-0.0309)	(-0.0188)	(-0.02505)	(-0.01273)	(-0.0514)

$$\underset{(n\times m)}{Y} = \underset{(n\times p)}{X}\ \underset{(p\times m)}{B} + \underset{(n\times m)}{E}$$

each independent variable; and E is a matrix of errors. We consider the regression coefficients, their significance level, and standard errors to understand the relationship between independent and dependent variables. Additionally, for each independent variable we consider type-II MANOVA's test - Pillai's statistic [9]. This statistic is useful in rejecting the null hypothesis that means of dependent variables are identical for the independent variable of interest. Intuitively, this test captures how useful an independent variable is in differentiating the dependent response variables.

An example of this analysis is in Table 1. The column vector corresponds to mode usage dependent variable while the rows contain independent variables. The analysis shows that both distance and frequency are useful in differentiating between various modes. This interpretation is based on the significant type-II MANOVA test reported in parenthesis underneath them in the table. Further, we see that closer the nearest bus stop is, the more likely it is that the person will walk. And, higher frequency of bus service greatly improves the usage of public transport. Both independent variables are negatively correlated with driving, as expected. In the following sections, we report on only the overall significance of factors due to space constraints.

4.3 Results: Static Factors

Static factors are the aspects of the transportation network, the individuals interaction with different modes, and their personality that do not vary from day to day.

4.3.1 Network factors. Network factors concern the transportation network around the home and workplace of the individual. Table 2 lists the factors by if they are significantly impact individuals mode choice. In agreement with existing literature, the number of transportation options available to an individual and the distance and frequency of nearby transit were all important for determining which modes people prefer. Other positive results that are less obvious in the literature is that peoples' mode choice is affected by their beliefs concerning the possibility of cycling to their typical destination. This belief was measured using a 7 point Likert agreement to the statement - *Cycling would be possible for at least part of my typical trips/commute (considering fitness, time required, road safety, space of bicycle on transit, and place to safely park a bike).* The Likert measurement can be considered a proxy for the how accessible bicycling is in the participant's transportation network.

Significant	number of options(***), distance from the nearest bus stop(.), frequency of bus service(*), distance from the nearest train station(*), frequency of trains(***), possibility of cycling(***)
Not-significant	*(none)*

Table 2: Network factors with categorized by significance in type II MANOVA tests. Significance codes for p-values: $*** < 0.001, ** < 0.01, * < 0.05, . < 0.1$

4.3.2 Personal Factors. Personal factors pertain to the individual and how they perceive and interact with the transportation network they are embedded in. Personal factors include the time and distance of peoples commutes, their previous experience with different modes, and how they value different characteristics of various modes. Table 3 lists the factors by if they supported as to being important for transportation mode choice. In agreement with previous research, the distance and time to work were both predictive of overall mode preferences. Also, the familiarity with the public transport system and knowledge of other options were important for predicting mode preferences. Individuals considerations of the health benefits, working en route, and parking also impacted their mode choice. We were surprised to see no effect from peoples attitudes toward sustainability, reliability and flexibility.

4.3.3 Personality Factors. Following recent work that suggests that personality may be inferred from online behavior [13] and may influence transportation choices [11], we also included three standard personality scales: TIPI [10], responsibility for events in their lives [2], and susceptibility to persuasion [5].

The majority of the dimensions of personality traits did not have support for predicting mode choice. We did not see an expected relationship between extroversion and public modes of transportation. Nor did we see any relationship between openness to new experiences and mode choice. The only Big 5 dimension that was predictive was conscientiousness (efficient v. easy-going). This was also supported in the responsibility dimensions with the only significant traits being anticipating the needs of others and taking others interest into account. Finally, the only supported dimensions of persuasion include reciprocity and consensus, but the findings for these were mixed with some versions of these traits showing no effect.

[2] http://ipip.ori.org/

Table 3: Network factors with significant codes: $*** < 0.001, ** < 0.01, * < 0.05, . < 0.1$

Significant	**Employment**	distance to work(***), commute time to work(***), familiar with public transport(**)
	Experience	familiar with public transport(**), have alternatives to driving(**), have tried faster(.), have tried ways to exercise(***)
	Mode characteristics	health benefits(.), can work en-route(**), avoid crowds(**), low risk of being late(**), parking(***), bicycle lanes(*)
Not-significant	**Experience**	have tried cheaper, have tried sustainable, would accept carpool invite, would try sustainable
	Mode characteristics	how long a mode takes, convenient departure times, flexible departure times, economy for me, sustainability, effort, comfort, connections, dependability, congestion, crime, accident injury risk, reliability of return, flexibility to change plans, carry heavy goods

4.4 Analysis: Dynamic Factors

Our traveler interview analysis suggests that dynamic factors such as purpose of the trip, weather, traffic etc. cause people to change mode preferences. Here we validate this finding as well as study how these factors affect mode preferences in a larger population sample. We extracted various scenarios from the traveler interviews that can have an impact on the mode choice for a trip. Our collection included: heavy traffic, heavy rain/snow fall, expecting alcohol consumption, accompanying child or infant, urgency, traveling while dark, planned grocery/shopping diversion, expecting parking problems, spare the air day, have an important appointment, hot weather, and pleasant weather. For each of these scenarios, we asked participants if they were more than 50% likely to select a mode to make a trip. The participant could pick multiple modes for each scenario. Additionally, mode usage (from previous sections) captures each participant does in the normal scenario. The scenarios are independent variables in our analysis and mode selection is the dependent variable.

4.5 Results: Dynamic Factors

We tabulated our data in a contingency table as shown in Figure 1. The horizontal axis has all the scenarios and the vertical axis has various modes. Each cell in the table represents the number of people who said that they will consider taking the corresponding mode under given scenario. As expected, most of the surveyed population drives in the normal scenario. This distribution changes as scenarios change. A Pearson's χ^2 test on this contingency table was significant with a p-value < 0.005 suggesting that mode selection is impacted by dynamic factors. Weather has a big impact; we see that people consider shifting to manual modes of transport in pleasant weather while snowy/rainy and hot weather shift the distribution towards private motorized modes. Similarly, concerns about parking and expected alcohol consumption tends to shift the distribution toward public transit and mobility services.

Table 4: Personality factors with significant codes: $*** < 0.001, ** < 0.01, * < 0.05, . < 0.1$

Significant	**TIPI**	dependable self-disciplined(**), disorganized careless(**)
	Responsibility	anticipate the needs of others(*), take others interests into account(.)
	Susceptibility to persuasion	reciprocate favors(.), rely on consensus for action(*)
Not-significant	**TIPI**	extroverted enthusiastic, reserved quiet, critical quarrelsome, sympathetic warm, anxious easily upset, calm emotionally stable, open to new experience, conventional uncreative
	Responsibility	return extra change by mistake, forgive and forget, be of service to others, act according to conscience, polite to strangers, appreciate people who wait on me, try not to think about the needy
	Susceptibility to persuasion	reciprocate gift, scarcity last to buy, scarcity special value, obey directions from authority, listen to authority, keep appointments, keep promises, take others' advice, inclined to believe someone I like, do favor for someone I like, help others, assemble furniture, identify with my country, identify with sports team, happy for the success of others

5 CONCLUSIONS AND DISCUSSION

Rapid worldwide urbanization coupled with new technologies from smart phones to dockless scooters to autonomous vehicles entering the marketplace creates a need for travel assistants. In this work, we present a framework for identifying what factors should drive the personalization of future traveler assistants. By first conducting open-ended qualitative interviews, we identify factors outside of existing literature. To test if these factor affect traveler behavior, we conducted a survey study whose results indicate the importance of static network, static personal, and static personality factors. Furthermore, we identified a set of dynamic factors (i.e., those that change from trip to trip) that impact mode choice. This study indicates that future travel assistants would benefit from personalization along a wider variety of dimensions than currently considered in the research community and the marketplace.

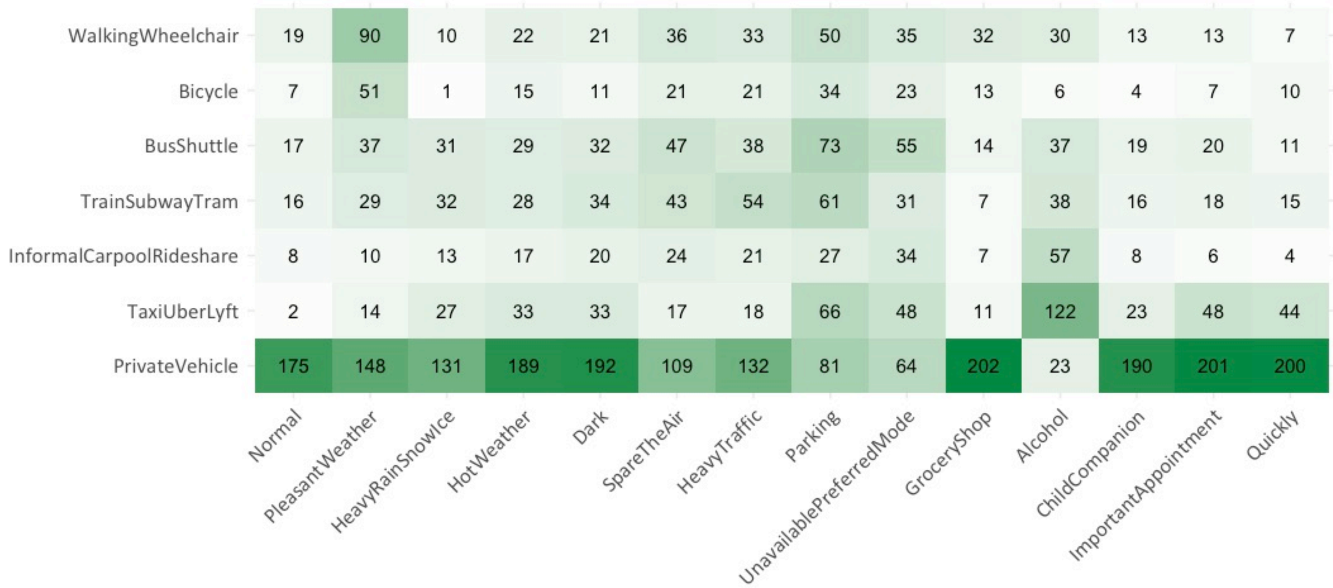

Figure 1: Impact of dynamic factors on usage of various modes.

In addition to helping individuals navigate their environment, understanding how people make transportation decisions could have a significant impact on a critical societal problem. Transportation is one of the largest consumers of energy in the world - in the United States, it accounted for 29% of energy consumption in 2016[3]. Many areas of urban transportation networks are underutilized while other areas are congested. Congestion alone in the United States wastes 6.9 billion hours and 3.1 billion gallons of fuel per year [17]. Recent work has begun looking at personalized incentives and routing recommendations to reduce energy consumption across regions [20][1][18][14]. By incorporating the factors we identify here, personalized mobility assistants could influence urban travelers to reduce congestion and conserve energy while promoting civic well being.

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