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Travel-based Multitasking: Modeling the Propensity of Northern Californians to Conduct Activities While Commuting

Authors
Berliner, Rosaria M
Malokin, Aliaksandr
Circella, Giovanni
et al.

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Rosaria M. Berliner
Institute of Transportation Studies
University of California, Davis
One Shields Avenue
Davis, CA 95616, USA
Phone: 1 347 871 2742
e-mail: aria.berliner@gmail.com

Aliaksandr Malokin
School of Civil and Environmental Engineering
Georgia Institute of Technology
790 Atlantic Drive
Atlanta, GA 30332, USA
Phone: 1 530 902 0498
e-mail: amalokin@gatech.edu

Giovanni Circella
School of Civil and Environmental Engineering
Georgia Institute of Technology
790 Atlantic Drive
Atlanta, GA 30332, USA
Phone: 1 530 554 0838
e-mail: giovanni.circella@ce.gatech.edu

and

Patricia L. Mokhtarian
School of Civil and Environmental Engineering
Georgia Institute of Technology
790 Atlantic Drive
Atlanta, GA 30332, USA
Phone: 1 404 385 1443
e-mail: patmokh@gatech.edu

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ABSTRACT

This paper investigates the choices to engage in various activities while commuting. Using data collected through a survey of 2149 Northern California commuters, we develop binary logistic regression models of the decision to engage in each of eight types of activities on the commute: rest/sleep, use a laptop, use a smartphone, listen to audio, read printed materials, edit papers/ printed materials, read electronic documents, and edit electronic documents. Explanatory variables include socio-demographic characteristics and attitudinal and time use factors. We model the engagement in each type of activity while traveling by each of five different modes (bicycle, commuter rail, transit, shared ride, and drive alone) – 33 models in all (excluding impractical combinations). The results illuminate the individual-specific traits affecting commuters' propensities to engage in activities while traveling. Those propensities exhibit large differences across modes. Longer commutes result in higher propensities to engage in almost all modeled activities for commuter rail and ridesharing. Age, gender, income, trip distance, education level, attitudes and preferences towards the adoption of technology, familial obligations, expectations about time use, and attitudes towards multitasking all affect the propensity to engage in activities while commuting.

Key words: Multitasking, Travel Behavior, Information / Communication Technology (ICT), Public Transportation, Time Use

1. INTRODUCTION

Multitasking refers to engaging in multiple activities "at the same time" (Bluedorn et al., 1992; Kaufman et al., 1991; Salvucci et al., 2009). Some people multitask to fit more activities into the fixed number of hours in a day, much as in a city skyline: when land (time) is limited, buildings (people) rise up (multitask) to compensate. Others multitask to distract themselves from an unpleasant task. Because of its prominence in a worker's daily activity pattern, the commute is often a magnet for multitasking, for these or various other reasons.

A number of studies have dealt with the subject of activities performed while traveling in general (sometimes referred to as "travel-based multitasking"), and commuting in particular. However, most of them have treated only one or a small number of modes (often transit), and most of them have been limited to a descriptive analysis of such activities. To our knowledge, very few studies have analyzed the personal and trip characteristics that influence the decisions to carry out activities while traveling on a specific mode, let alone done so for multiple modes. Addressing that gap is the purpose of the present paper. In addition to modeling the decision to engage in various activities while commuting, we are especially interested in exploring how the activities performed by commuters who choose active-attention modes, e.g. driving or cycling, differ from those of commuters traveling on passive modes, e.g. bus or train.

The present paper is part of a larger investigation of activities conducted while traveling – specifically, while commuting. Launched in late 2011, the study at large is exploring a number of research topics, including how such activities (especially the use of smartphones, tablets, and other portable electronic devices) affect individuals' mode choice and valuation (both monetary and subjective) of travel time. Specifically, we designed and administered a survey that collected information about commuters' engagement in multitasking, and a variety of potentially relevant variables such as socio-demographic traits, attitudes, personality traits, and mode choice.

In the present research, we build binary logistic regression models, with these other variables as model inputs, of an individual's propensity to engage in eight types of activities while commuting on five different modes: bicycle, commuter rail, transit (bus, subway, and light rail), shared ride, and drive alone. The eight types of activities are rest/sleep, use a laptop, use a smartphone, listen to audio, read printed materials, edit papers/printed materials, read electronic documents, and edit electronic documents. In addition to investigating the drivers behind the adoption of travel-based multitasking, this research is also instrumental to our separate analysis of the influence of multitasking on commute mode choice, using the same data (see Malokin et al., 2019).

The remainder of this paper is organized as follows. Section 2 presents a brief review of previous related research, particularly focusing on studies that have modeled the engagement in activities while traveling. Section 3 describes the background of the study, and provides details on the data collection process. Section 4 presents the model specifications and discusses the results. Lastly, Section 5 offers some conclusions and perspectives for further research.

2. LITERATURE REVIEW

Circella et al. (2012) developed a typology of multitasking, which discusses different possible combinations of activities carried out "at the same time" based on the *share of time* and *share of resources* that are dedicated to the activity. In particular, they distinguished *overlaying* multiple activities simultaneously, *interleaving* multiple activities, where at least one is active at a reduced level "in the background" while another is active "in the foreground", and *switching* between multiple activities, in which only one is active at a time. "Travel-based multitasking" would usually be classified as the first type, overlaying activities onto a trip (although, depending on the time granularity, it could also be viewed as interleaving other activities with those required for making the trip).

In this paper, we consider commuting as the primary activity, which can be overlaid by one or several secondary activities. Since multitasking can make the primary activity more efficient and/or pleasant, it can affect travelers' evaluation of the utility of travel time (Ettema and Verschuren, 2007).

Certainly, the increased adoption of information and communication technologies (ICTs) has contributed to changing the way individuals organize their activities. It has also influenced the way they travel (for a more complete discussion of the many impacts of ICT on transportation, see Salomon, 1986; Mokhtarian, 2009; Choo and Mokhtarian, 2005; and Circella and Mokhtarian, forthcoming). Smartphones, laptops, tablets and other portable internet-enabled devices have presented new possibilities to work and be entertained while commuting – more simply, ICTs have increased commuters' ability to multitask.

Several studies have investigated the activities travelers conduct during their trips, and the relationships of those activities to the possession of specific ICT devices. Through the analysis of data from Great Britain's 2004 National Rail Passengers Survey Lyons et al., (2007) reported that a large portion of respondents believed that having an electronic device in their possession would make the time pass more quickly. Susilo et al. (2012), using responses from the 2010 wave of the same survey, reported that almost a third of commuters worked during their commute, showing an increase of 4 percentage points in comparison with the 2004 measurement. They suggest that lightweight e-readers could have played a role in this increase. Schwieterman and Battaglia (2014) observed that personal ICT usage on intercity buses (e.g. Greyhound), discount buses (e.g. Bolt Bus and Megabus), Amtrak intercity trains, and airplanes has increased over a 4-year period, with the fastest growth on intercity buses but the highest levels on discount buses. Specifically, personal ICT usage on intercity buses grew from 17.9% to 43.6% (Schwieterman and Battaglia, 2014), while discount buses, starting from a higher level, grew the slowest: 38.7% to 46.4% from 2010 to 2013.

Although several studies have descriptively looked at which activities were performed during an individual's commute, fewer have tried to explicitly model the engagement in these activities. Guo et al. (2013) estimated a multinomial logit (MNL) model of the probability of using an ICT device (smartphone/iPad, iPod, or none) while riding to or from the University of British Columbia (UBC), exploring the impact of travelers' age, gender, total travel time, movement roughness, and physical location on the bus. They found that females are less likely to use MP3 players and cell phones during their trip, while young travelers are more likely to use them, in addition to smartphones and tablets. Interestingly, on their inbound trip UBC community members are statistically more likely to use their MP3 players and less likely to use their smartphones and tablets, apparently preferring to relax by listening to music, rather than working on their way to class or work. Frei and Mahmassani (2011) used binary logit models to separately predict the use of cell phones/ personal digital assistants (PDAs), printed material, and audiovisual devices while riding Chicago Transit. They found that females are less likely than males to use cell phones during their commute. Waerden et al. (2009) used observational data to estimate an MNL model of the probability of doing different activities on Dutch trains. The activities modeled included reading printed materials, talking (to another passenger or on the phone), and combined activities (e.g. listening to music while reading, or reading and talking). They found that engagement in travel-based multitasking is influenced by individual (age) and environmental (accompanying persons, temporal alignment of a trip, mode and crowdedness) characteristics. Zhang and Timmermans (2010) used a scobit model on a 2008 sample of 523 Japanese bus riders to predict observed multitasking behavior during the travel episode, as a function of age, gender, in-car experience, travel time and cost, and temporal arrangements. They reported that the probability to engage in an activity is proportional to in-vehicle travel time.

These previous studies focused only on certain types of activities performed while traveling on selected public transit modes. Our study further expands this field of research, through systematically modeling travel-based multitasking for a large number of activity-mode combinations. In particular, we distinguish between "active-attention" (requiring increased involvement during the trip) and "passive" modes. Moreover, using a very rich dataset, we are able to investigate the impact of a large number of socio-demographic traits and attitudinal variables, to better illuminate the driving forces behind the decisions to engage in secondary activities while traveling. We expect the results to be of interest to scholars in the travel behavior and multitasking research fields, as well as to public transit operators and vehicle manufacturers.

3. EMPIRICAL CONTEXT

As mentioned, the empirical analysis of this study is based on a comprehensive survey, which was distributed in both paper and online forms to commuters in Northern California. Several strategies were employed to recruit the sample; additional details about the survey design and data collection can be found in Neufeld and Mokhtarian (2012). The survey, which was 14 pages long in the printed version, included nine main parts:

- Parts A, B, and C obtained respondents' opinions on a number of topics, including views about themselves and their personal attitudes and preferences, their opinions on multitasking, and some aspects of their daily lives.
- Part D specifically targeted respondents' views on waiting.
- Part E investigated perceptions of several commute mode options.
- Part F collected information about a recent commute trip.
- Part G asked hypothetical questions about the response to free Wi-Fi on transit.
- Part H asked about respondents' commutes in general.
- Part I collected respondents' socio-demographic and socio-economic information.

Table 1 summarizes selected descriptive statistics of the sample. Given the specialized nature of the population ("Northern California commuters"), it is difficult to make definitive comparisons between sample and population, and our goal was not to achieve representativeness of the population but rather sufficient diversity on characteristics of interest to facilitate stable estimation of relationships. The person with average characteristics for this sample is female, around 45 years old, a college graduate, and in a household of 2.7 people owning 2.1 vehicles and earning $75,000 - $99,999 annually.

TABLE 1 Selected Characteristics of the Sample (N=2149)

Characteristic (sample size)	N (%)	Characteristic (sample/pop. size)	N (%)
Gender (2135)		**Annual household income (2104)**	
Female	1319 (61.4)	Less than $25,000	121 (5.6)
		$25,000 to $49,999	306 (14.2)
Age (2139)		$50,000 to $74,999	425 (19.8)
18 to 24	97 (4.5)	$75,000 to $99,999	412 (19.2)
25 to 40	729 (33.9)	$100,000 to $124,999	355 (16.5)
41 to 64	1228 (57.1)	$125,000 or more	485 (22.6)
65 to 74	76 (3.5)		
75 or older	9 (0.4)	**Sample mode shares (2149)**	
		Biking	178 (8.3)
Education level (2149)		Commuter rail	173 (8.1)
Some grade/ high school	3 (0.1)	Transit[a]	649 (30.2)
High school diploma	59 (2.7)	Shared ride[b]	342 (15.9)
Some college/ technical school	489 (22.8)	Driving alone	807 (37.6)
4-year college degree	693 (32.2)		
Some graduate school	231 (10.7)	**Characteristic (sample size)**	**Sample mean**
Complete graduate degree(s)	674 (31.4)		
		Household size (2142)	2.67
Occupation (2143)			
Clerical/ administrative support	326 (15.2)	**Number of operational household vehicles (2136)**	2.07
Homemaker	8 (0.4)		
Manager/ administrator	361 (16.8)		
Production/ construction	32 (1.5)		
Professional/ technical	1087 (50.4)		
Sales/ marketing	78 (3.6)		
Service/ repair	45 (2.1)		
Student	184 (8.6)		
Other	26 (1.2)		

[a] Includes local bus (current share 0.0549), express bus (0.0707) and light rail/subway (0.1764).
[b] Includes car/van driving with passengers (current share 0.0721), and carpool/vanpool/shuttle passenger (0.0871).

4. MODELING ENGAGEMENT IN ACTIVITIES WHILE COMMUTING

We modeled the mode-specific propensity to engage in eight types of activities while commuting (dependent variable = 1 if an activity reported, 0 otherwise): paper reading (reading printed materials), paper writing (writing with a pencil or pen), electronic reading (reading from screen), electronic writing (writing/editing an electronic document or text), laptop (using a laptop/tablet/ netbook), audio (listening to audio), smartphone (using a smartphone), and rest (resting or sleeping). This posed a problem, however. We only know that a reported activity occurred during the commute, but nearly half (about 49%) of commutes are multimodal, and for such commutes we do not know on which mode the reported activity occurred. However, respondents were asked to report their "primary commute mode" (i.e. "the one that was used for most of the trip"), and in our models we associated the reported activities with this mode. This contributes a certain amount of noise to the models, since some activities will have been incorrectly associated with the primary mode instead of the secondary one on which it actually occurred.[1] Five categories of primary commute mode were identified: bicycle, commuter rail, transit, shared ride, and drive alone.

The prospective explanatory variables consist of socio-economic traits, individual attitudes, personality traits, polychronicity (one's preference for multitasking), and work and commute characteristics. The constant term of each model captures the average net impact (on the utility of conducting the activity versus not) of all unobserved characteristics, including the inherent conduciveness of the mode to performing the modeled activity. Each activity model was estimated at most five times, on the respective subsamples of individuals choosing each mode. A combination of conceptual and statistical considerations guided model estimation.[2]

From a total of 40 model candidates (8 activities performed across 5 modes), 7 are estimated as market share models (i.e. containing only a constant term) on the basis of low observed engagement or failure to identify any statistically significant explanatory variable, and hence not presented here. The remainder, 33 fully-specified models, had adjusted $\boldsymbol{\rho^2}$ goodness-of-fit measures (Ben-Akiva and Lerman, 1985) ranging from 0.06 to 0.87. Since we chose the equally-likely base for the $\boldsymbol{\rho^2}$ measures, they will be influenced by the market shares, with activities having the most unbalanced shares tending to exhibit the highest $\boldsymbol{\rho^2}$s.

Figure 1 presents observed average engagement (for the mode choosers), the predicted average engagement (of the whole sample), and the model goodness of fit for each of the 33 mode-activity combinations (sample sizes may vary due to missing data on the variables significant in each final model, but the approximate sizes are given by the number choosing each mode as shown in Table 1). In general, observed engagement rates are similar to predicted rates. However, the former tends to be substantially higher than the latter for the last five activities and the rail mode. This indicates a selectivity mechanism at work: either those with a greater propensity to conduct those activities on their commute are more likely to choose rail to facilitate conducting them, or those with a greater propensity to choose rail are more likely to perform activities facilitated by rail. Overall, audio and smartphone have the highest propensities to be conducted, but as would be expected, there are large differences across mode in the propensity to conduct most of the activities.

[1] This may well be true for many of the cases involving unusual combinations such as using a laptop/tablet while riding a bike or driving alone, but we also note that most of us have personally witnessed many if not all of these combinations, even if thankfully rarely in some instances.
[2] In support of the companion study (Malokin et al., 2019), the estimated models were then applied to predict the conditional probability of conducting that activity on that mode for *all* respondents, not just the choosers of that mode. Those predicted mode-specific propensities to conduct each activity were then included as explanatory variables in a model of mode choice.

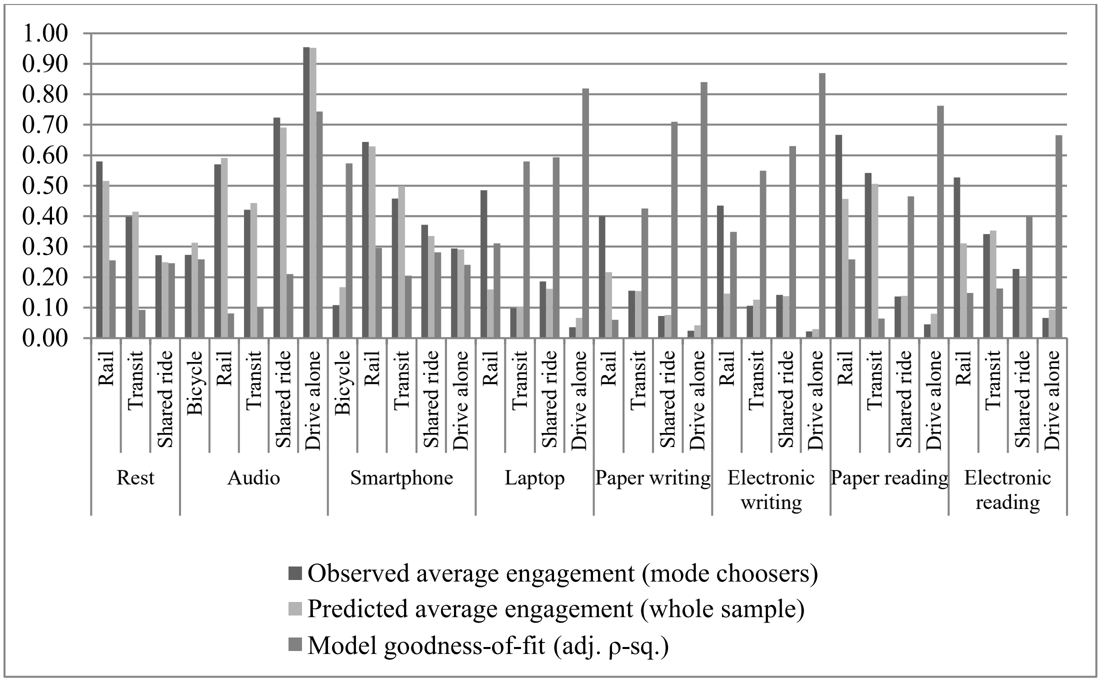

FIGURE 1 The observed average engagement, predicted average engagement (propensity), and adjusted ρ^2 for each activity-mode combination

Tables 2, 3, and 4 summarize the impact of three groups of explanatory variables on the propensity to engage in each of the eight activities while commuting, comparing them side-by-side across modes and activities. Table 2 deals with key socio-demographic characteristics of the respondents and their households, Table 3 with attitudes, and Table 4 with work- and commute-related variables. Due to space constraints and the large number of estimated models, we focus the discussion on some of the most prominent impacts.

The tables are designed to condense a large amount of information into a compact form. Statistically significant variables having positive coefficients are coded with capital letters according to the notation provided in the first column, and significant variables with negative coefficients are coded with capital letters enclosed in parentheses (following the convention for negative numbers in accounting). The number of letters for a given entry denotes the level of significance of the associated coefficient, with three letters meaning $\boldsymbol{p < 0.01}$, two for $\boldsymbol{0.01 < p < 0.05}$, and one for $\boldsymbol{0.05 < p < 0.10}$. For example, the upper part of Table 2 shows that the variable "Number of people in the household," denoted by the letter N, is significant in three models: bicycle commuters for audio, shared ride commuters for audio, and transit commuters for resting. For all three models, the table reads "NN" indicating that the number of people in the household has a positive coefficient, which is significant at the 0.05 level. This means that, for example, bicycle commuters who come from larger households have a higher propensity to listen to audio than bicycle commuters who come from smaller households. The specific coefficient estimates and other information for each model are available from the authors.

4.1 Socio-Demographic Variables

As seen in Table 2, gender is significant to every ICT-based activity except reading electronically. Women taking commuter rail or transit are less likely than men (ceteris paribus) to use laptops during their commute. Similarly, women who rideshare are less likely to write using electronic devices; however, female bicyclists are more likely to listen to audio and use their smartphones during their commute. Thus, there is a clear gender distinction within mode and activity purpose dimensions, with men being more likely to engage in productive activities that involve using a laptop and writing electronically on modes that are conducive to them, whereas women are more prone to engage in entertainment ICT-based activities while biking – a mode not suitable for more productive activities. Finally, we found no gender association with the propensity to be involved in traditional non-ICT activities.

Age affects the propensity to engage in six of the eight activities modeled. Not surprisingly, older people tend to read using “traditional” media (e.g. books or other printed material), probably because of lower familiarity with (and hence possession of) technological devices. They are less likely to read electronically, or use smartphones or laptops during their commute on various modes – a clear indication that older commuters are usually less inclined to use ICT devices. Conversely, younger travelers are more likely than their elders to use smartphones while traveling on transit, ridesharing, and/or driving alone.

More-educated travelers have a greater propensity to read printed materials, write traditionally or electronically, or use a smartphone when using a passive mode of transportation. It is likely that such individuals are working during their commute – perceiving it as otherwise wasted time that, if used productively, can save time elsewhere during the day. Although very few people (about 7%) read electronically while driving alone, educated commuters who drive alone are less likely than other solo drivers to read electronically during their commute, perhaps due to a heightened awareness of safety concerns.

TABLE 2 Socio-Demographic Variables Significant in the Activity-Mode Models

Variable	Mode	Activity							
		Paper Reading	Paper Writing	Electronic Reading	Electronic Writing	Laptop	Audio	Smart-phone	Rest
	Bicycle						NN		
B: Number of bikes in household	Commuter rail	(BB)							(LLL)
C: Has children below age 6 in HH	Transit								NN
L: Number of other licensed drivers in household	Shared ride						NN		
N: Number of people in the household	Driving alone					CC			
	Bicycle						FFF	FF	
A: Age	Commuter rail	AA EEE				(FF) (AAA)			(AAA)
E: Education level	Transit	AAA EE				(FF)	(AAA)	(AAA)	
F: Female	Shared ride		EEE	(AA)	(FF) EEE	(AA)		(AAA) EE	
	Driving alone			(EEE)				(AAA)	
	Bicycle								
P: Percent of time the vehicle is available	Commuter rail								SS PP
S: Has a person in HH who needs special care	Transit							(VVV)	
V: Vehicle age	Shared ride								
	Driving alone	(PPP)	(PPP)	(PPP)		(PPP)			
	Bicycle								
I: Lived abroad for more than a year	Commuter rail				(HHH)				
L: Immigrant * low income	Transit		LL HHH						III
M: Immigrant * medium income	Shared ride		MMM		MM				
H: Immigrant * high income	Driving alone								
C: Self-employed/contractor job	Bicycle								
H: Hourly-waged employee ***M: Managerial job***	Commuter rail	OO			(HHH) PPP	(HHH)			
O: Conventional job schedule ***P: Part-time job schedule***	Transit		CCC					MM UU	
S: Sales job	Shared Ride								(MMM)
U: Unconventional job schedule	Driving alone							SS	
	Bicycle								
H: Household income	Commuter rail	(HHH)			PP				
M: Household median income	Transit		(PP)	HHH			(PP)	HHH	
P: Per capita income	Shared Ride	(PPP)		MMM	P	PPP		MMM	
	Driving alone							HHH	

With their extra disposable income, higher-income individuals have greater access to ICT devices than lower-income individuals. Thus, in terms of the "lower technology" activities, such as paper reading or writing and audio, per capita income has a negative effect on the propensity to engage in these activities. More specifically, individuals from higher-income households who are commuting by passive modes (commuter rail, transit, and rideshare) are less likely to use printed materials or listen to audio during their commute; instead, such individuals are more likely to use a laptop or write electronically, especially when ridesharing or using commuter rail.

4.2 Attitudinal Variables

The numerous attitudinal, lifestyle, and personality statements in the survey were factor-analyzed in blocks, and the factor scores are incorporated as explanatory variables into the models. Table 3 presents the attitudinal variables that are statistically significant to the eight modeled activities.

Individuals who are pro-technology are more likely than others to use technological devices during their commute; notably, they are more likely to use smartphones in all five mode-specific models. Similarly, pro-technology individuals using transit are more likely to read or write electronically, use a laptop, or listen to audio, and less likely to read using printed materials.

Individuals who like active modes of transportation (i.e. bicycling or walking) are less likely to rest during a transit or rail commute, perhaps signifying a desire to be as active as possible, even on a passive mode. Those who do not mind occasionally giving up a day's pay to take a day off from work (which may be a proxy for a less work-oriented and/or more leisure-oriented lifestyle) are less likely to use a laptop during their commute (on commuter rail or while driving alone) and more likely to listen to audio while biking (a major distinction between productivity-oriented and entertainment activity purposes).

Those who own (or want to own) a "car that impresses other people" may be oriented toward displaying affluence, which could explain why they are more likely to read electronically and/or use a smartphone even on transit (and less likely to read paper materials on commuter rail). The same acquisitive lifestyle may explain their greater tendency to listen to audio if they rideshare or drive alone, and even to use a laptop or tablet if driving alone.

Similar to their opinions, individuals' personalities affect their propensity to engage in certain activities while commuting. As expected, frugal solo drivers and transit and commuter rail passengers were less likely than their less frugal counterparts to use a smartphone or read electronically – both activities that require purchased devices. Frugal rail commuters were also more likely to rest during their commute.

TABLE 3 Attitudinal Variables Significant in the Activity-Mode Models

Variable	Mode	Activity							
		Paper Reading	**Paper Writing**	**Electronic Reading**	**Electronic Writing**	**Laptop**	**Audio**	**Smart-phone**	**Rest**
N:* *Travel is wasted time ***O:* *Does not mind taking a day off without pay*** ***P:* *Time pressure is preferred*** ***R:* *Time pressure is a reality*** ***T:* *Usually goes to the closest store*** ***S:* *Does not mind being stuck in traffic***	Bicycle						OO		
	Commuter rail				(RRR)	(OO)			
	Transit							PPP	
	Shared ride			NN		NNN	(RRR) TT SSS		
	Driving alone	(PP)				(O)		SS	
A:* *Likes active modes of transportation ***B:* *Only good thing about a job is it pays the bills*** ***C:* *Pro-technology*** ***I:* *Impressive car*** ***J:* *Satisfied with life/job***	Bicycle						CCC	CCC	
	Commuter rail	(II)		CCC AAA				CCC (JJ)	(AA)
	Transit	(CCC)		CCC II	CCC	CCC	CCC	CCC II	(AA)
	Shared ride	AAA		CCC		AA	III	CCC	BB
	Driving alone			CCC		II	II	CCC	
E:* *Explorer ***F:* *Frugal*** ***O:* *Organized*** ***R:* *Risk taker*** ***T:* *Trendsetter*** ***V:* *Extrovert***	Bicycle								
	Commuter rail				TT		RR	TTT (FFF)	(EE) F
	Transit			(FF)		RR			
	Shared ride		OO					(EE)	
	Driving alone	EE				VV		TTT (FF)	
M:* *Polychronic ***N:* *Background noise is not a distraction***	Bicycle								
	Commuter rail						NNN		
	Transit					MMM	NNN	N	(MM)
	Shared ride		MM				NNN		
	Driving alone				MMM				
E:* *Welcomes waiting ***N:* *Likes to do nothing while waiting*** ***Q:* *Expected and equipped waiting*** ***U:* *Unplanned wait time***	Bicycle								
	Commuter rail								EEE
	Transit	(UU)						(NN)	NNN
	Shared ride						(NN)		
	Driving alone						QQQ	(NN)	

On first thought, one might expect polychronic individuals (those with a high general inclination toward multitasking) to engage in almost all modeled activities, except resting. Consistent with that expectation, self-identifying polychronic commuters are less likely to rest and more likely to use a laptop if taking transit. Similarly, more polychronic shared ride and drive alone commuters are respectively also more likely to write with paper and pen, or write electronically during their commute, compared to the other users of the same mode. However, these are the only statistically significant relationships for this variable. We speculate that monochronic individuals do not see the routine commute as a distraction competing for their attention, but rather as a passive background over which an active task can easily be laid. Therefore, to the extent that both mechanisms are at work simultaneously in the sample, a polychronic orientation may have little to no influence, overall, on the decision to conduct certain activities while commuting. On the other hand, for those who do not view background noise as a distraction, it is unsurprising that they have a higher propensity to listen to audio if using commuter rail, transit, or ridesharing, and to use a smartphone if taking transit.

Among the attitudes toward waiting, the factor score capturing a willingness to do nothing while waiting has a logical but interesting impact pattern in the mode-activity matrix. Commuters who are willing to do nothing while waiting have a higher propensity to rest on transit and a lower propensity to use a smartphone (than others on transit and while driving alone) or listen to audio (on shared ride), indicating a cohort of people who have little need for ICT devices to keep them productive or even simply entertained while commuting.

4.3 Time Use and Commute-specific Variables

Table 4 presents the work and commute variables that affect the propensity to engage in the eight modeled activities.

The desire or obligation to be available to others affects individuals' propensities to engage in certain activities during their commute. The possession of ICT devices allows those who want or need to be constantly available to others to stay connected. Those who must be available to others during their commute are more likely than others to write digitally if ridesharing or commuting on transit, and to use their smartphone if driving alone. But they are less likely than others to rest if on commuter rail – they must remain connected to the world at all times and they may be texting or sending emails during this period. Similarly, as a way to stay connected, those who would like to be available to others during their commute are more likely than others to read electronically, use their laptop, or use their smartphone if ridesharing, write electronically if on commuter rail, or use their smartphone if on transit. Transit commuters who want to be available to others are less likely than others to read printed materials during their commute – this could be indicative of these individuals trying to remain available and connected by way, for example, of their smartphone or internet enabled device.

Those who *want* to do recreational activities on their commute are more likely than others to read electronically if ridesharing or driving alone, and to read paper materials if on commuter rail or transit. They are more likely than others to use their smartphone, but less likely to write electronically, if driving alone. They are more likely to use their laptop if ridesharing, and less likely to rest if on commuter rail. Relatively few (135 of 807) respondents who drive alone as their primary commute mode feel that they "*have*" to do recreational activities on their commute, but those who do are more likely than others to read printed materials or use their laptops or tablets.

TABLE 4 Time Use and Commute-specific Variables Significant in the Activity-Mode Models

Variable	Mode	Activity: Paper Reading	Paper Writing	Electronic Reading	Electronic Writing	Laptop	Audio	Smart-phone	Rest
	Bicycle						BBB		
	Commuter rail				BB				(AAA)
A: Has to be constantly available to people	Transit	(BBB)			AA			BB	
B: Would like to be constantly available to people	Shared Ride			BBB	AAA	BBB		BBB	
	Driving alone							AAA	
	Bicycle								
R: Has to do recreation on commute	Commuter rail	SS							(SSS)
S: Would like to do recreation on commute	Transit	SS							
	Shared Ride			SSS		SS			
	Driving alone	RRR		SS	(SS)	RRR		SS	
	Bicycle								
	Commuter rail				WWW	WWW			
W: Has to work on commute	Transit	WWW	WWW	XX	XXX			WW	
X: Would like to work on commute	Shared Ride	WW	WWW	XXX	WWW	WWW	(XXX)		
	Driving alone	WWW	W		WWW	WW			
	Bicycle								
	Commuter rail				(NN)				
M: Has to multitask at work	Transit								
N: Would like to multitask at work	Shared Ride	(MMM)				(MMM)			(MM)
	Driving alone				(MMM)		NNN		
	Bicycle							RR	
R: Has to take the same route ***S: Would like to take the same route***	Commuter rail	SSS							TTT WW
T: Spending time on traditional/ social activities	Transit	TT	WWW						
W: Feeling of amount of time working	Shared Ride								
	Driving alone								
	Bicycle								
D: Travel distance	Commuter rail	DDD	DDD	DDD	DDD FFF	DDD			DDD
F: Days per week commuting	Transit				DDD				DDD
	Shared Ride	DDD	DDD		DDD	DDD			DDD
	Driving alone				DD				

Not surprisingly, individuals who *must* work on their commute have a higher propensity than others to read and write with printed materials if on transit, ridesharing, or driving alone; to write electronically or use a laptop if on commuter rail, ridesharing, or driving alone; and to use a smartphone if on transit. Those who would *like* to work on their commute have a higher propensity than others to read or write electronically if on transit, and to read electronically if ridesharing; they have a lower propensity to listen to audio while ridesharing. Ironically, respondents who have to multitask *at work* are *less* likely than others to multitask while traveling, at least in terms of resting, reading printed materials, and using a laptop if ridesharing, or writing electronically if driving alone. Moreover, rail commuters who would like to multitask at work are less likely to write electronically during their commute. Those who want to multitask at work are more likely to listen to audio during their drive alone commute, which may indicate the desire to carry a complex lifestyle from work into their private lives as well, or conversely may reflect a need to relax after a high-complexity workday.

The last prominent variable in this table is travel distance. It is intuitive that a longer trip increases the propensity to engage in any number of activities. This is especially true for electronic writing, where trip distance is statistically significant for all modes except bike, i.e. a productive activity such as electronic writing can be performed if there is enough time for it. For commuter rail passengers, trip distance is statistically significant for all but two activities, smartphone and audio – both of which are relatively easy to start and stop on shorter trips.

5. CONCLUSIONS

The aim of this study was to investigate the factors influencing the decision to engage in each of eight activities while commuting on one of five primary modes. Using data collected from 2149 commuters in Northern California, we estimated binary logit models of the propensity to engage in each of 33 mode-activity combinations, with a rich set of attitudinal and socio-economic measures available as explanatory variables.

We found numerous factors related to an individual's propensity to engage in different activities, including the obvious socio-demographic variables such as age, gender, and income, and less-obvious personal characteristics such as risk-taker or trendsetter. Other significant factors include trip distance as well as work expectations and obligations. The large number of significant results precludes a full recapitulation here; however, we highlight a few that may be of particular interest.

Consistent with the findings of Frei and Mahmassani (2011) and Guo et al. (2013), we found that women are less likely than men to use technology during their commute – in this case, females are less likely to engage in electronic writing if ridesharing, and laptop usage if using transit or commuter rail. Personality traits (e.g. frugal, explorer, extrovert) also influence the activities conducted while commuting; for example, as expected, frugal individuals are less likely than others to engage in activities that require purchasing an expensive device such as a laptop or smartphone.

The influence of multitasking-related variables is complex and interesting. For example, respondents who are required to multitask *at work* are *less* likely than others to multitask while commuting, at least in terms of resting, reading printed materials, and using a laptop if ridesharing, or writing electronically if driving alone. Those who self-identify as polychronic (inclined to multitask), are more likely than others to engage in "productive" activities on various modes and less likely to rest on transit. However, overall there are fewer significant relationships than might be expected for this variable, perhaps because travel, especially on passive modes, is an activity that lends itself to having activities overlaid onto it, reasonably easily even for monochronic commuters. Finally, trip distance positively impacts an individual's propensity to engage in almost all activities for one or more modes.

As mentioned in the introduction, this research is part of a larger effort involving the estimation of mode choice models that incorporate these mode- and activity-specific propensities to multitask as explanatory variables (Malokin, et al., 2019). Later analysis of this extensive and unique dataset will explore the reported benefits and disadvantages of conducting the reported activities; relating these to the activity-mode combination in question and to the personal characteristics used in the present study will provide important insight into the motivations for travel-based multitasking (or not). It would also be of interest to cluster analyze the sample, to identify groups of individuals with similar profiles. A number of such analyses would be pertinent, such as identifying common clusters of conducted activities and then investigating socioeconomic and attitudinal differences between clusters. It would also be of interest to segment the models along a number of possible dimensions, such as polychronicity attitudes. Beyond the current sample, it would be of great interest to gather similar data in diverse countries and urban contexts, to begin to understand the likely cultural and geographic differences in factors affecting the choice to conduct specific activities while commuting on specific modes.

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