Multitasking while Driving: A Time Use Study of Commuting Knowledge Workers to Assess Current and Future Uses*

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Abstract

Commuting has enormous impact on individuals, families, organizations, and society. Advances in vehicle automation may help workers employ the time spent commuting in productive work-tasks or wellbeing activities. To achieve this goal, however, we need to develop a deeper understanding of which work and personal activities are of value for commuting workers. In this paper we present results from an online time-use study of 400 knowledge workers who commute-by-driving. The data allow us to study multitasking-while-driving behavior of commuting knowledge workers, identify which non-driving tasks knowledge workers currently engage in while driving, and the non-driving tasks individuals would like to engage in when using a safe highly automated vehicle in the future. We discuss the implications of our findings for the design of technology that supports work and wellbeing activities in automated cars.

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1. Introduction

In major cities around the world, daily commute time is over an hour (Kalia, 2018, Lyons and Chatterjee, 2008). According to the US Census Bureau, U.S. workers commute to and from work for an average of about 50 minutes a day, with approximately 25 million workers spending more than 90 minutes commuting each day and about 600,000 workers traveling at least 90 minutes each way (McKenzie and Rapino, 2011). While often necessary, commuting is also seen as a costly activity, that increases the amount of wasted fuel per auto commuter and crowds out time that could be allocated towards other productive activities. Research also indicates that people with long commutes are less productive at work, more exhausted, and report lower job satisfaction (Gino et al., 2017).

Workers very often commute to work by driving, which is a task that requires the driver's visual attention to observe the road, and manual action to control the vehicle. As of 2021, such constant supervision is required to operate all commercially available vehicles. In some advanced vehicles, automated systems support the driver: adaptive cruise control maintains vehicle speed and adjusts it to avoid collision with slower moving vehicles in front; automated steering helps keep the vehicle within the lane. However, even when automation is on, in today's vehicles the driver must maintain attention on the outside world and be ready to assume full control of the vehicle at any moment (SAE J3016, 2016).

This situation is about to change. The next step in the progress of automation will introduce vehicles that will be capable of driving without the intervention of a human driver. These vehicles will only be self-driving for relatively short periods of time, when the automation can manage the road conditions (e.g. at low speeds during bumper-to-bumper driving on multi-lane highways). Still, during these limited time periods the driver will not need to always keep their eyes on the road. Instead, they will be able to safely engage in some non-driving tasks (Kun et al., 2016).

What will drivers do with these opportunities to engage in non-driving tasks during their commutes? There are two parts to this question. First, what do drivers want to do with the newly available time, i.e. how would drivers like to reallocate the time that they currently reserve for driving? To the extent that they might decide to engage in both work-related and non-work-related tasks, these decisions will have impact on their work productivity as well as on their general wellbeing. Second, which of the desired non-driving tasks are safe to perform in automated vehicles? The first automated vehicles to appear on our roads will have significant technical limitations. Thus, they will often require drivers to take back control from automation, and they will leave little time for the driver to do this–perhaps as little as 10 seconds. Switching between the non-driving and driving tasks is a complex process (Janssen et al., 2019). The driver must be able to switch their visual attention away from the non-driving task back to driving, understand the context of the driving task (from traffic situation, to the weather, to the driver's target destination), and take physical control of the vehicle. Completing this transition between non-driving to driving tasks quickly means that the non-driving task must not unduly burden the driver's visual attention during the transition, and that the non-driving task must allow the driver to quickly engage their hands to control the steering wheel (and their feet to control pedals). In this work we address both of these questions.

While existing work examines personal and societal impact of highly-automated vehicles, e.g.(Harb et al., 2018, Kim et al., 2020, Dannemiller et al., 2021), our focus is primarily on exploring how drivers might want to utilize newly available time while driving in automated vehicles. This exercise allows us to evaluate the extent to which the non-driving tasks of interest in automated vehicles might require the driver's visual attention and the use of their hands, and thus inhibit their ability to resume manual control of the vehicle.

Our investigation focuses on the case of knowledge workers. The term "knowledge worker" was coined by Peter Drucker, who is considered to be one of the founders of modern management (Webster Jr, 2009). The term refers to workers who are focused on problem-solving, and who are not tied to a particular facility (such as a factory) to perform their job (Drucker, 2012). Knowledge workers are a heterogeneous group that includes professionals such as executives, engineers, and sales people. This is a particularly interesting group of individuals for our purposes: since their ability to perform primary work activities is not–in principle–tied to a specific work location, this is a category of workers that is most likely to be able to use the time spent commuting in an automated vehicle engaging in work activities.

We base our analysis on data collected in an online time-use study of 400 knowledge workers who commute-by-driving. We use these data to shed light on current and expected multitasking behavior and non-driving tasks of knowledge workers, and to inform the design of human-computer interfaces for increasing the productivity and wellbeing of commuting workers. More specifically, we make the following contributions: 1) we identify how commuting knowledge workers currently allocate their time to commuting and other activities, and relate this to their life satisfaction; 2) we identify the work-related and personal non-driving tasks that commuting knowledge workers currently engage in when they drive to and from work; 3) we provide quantitative measures of the engagement in non-driving tasks during driving commutes in two ways: (a) we identify if they occur during the morning or afternoon commute, and (b) how often they are likely to occur during a commute; 4) we provide quantitative safety-related measures of engagement in non-driving tasks in two ways: (a) how likely is it that a driver will engage in at least one non-driving task as well as how likely it is that they will engage in multiple non-driving tasks, and (b) which non-driving tasks require visual attention and the use of hands; 5) we identify non-driving tasks that individuals would like to engage in when commuting in a safe, highly automated vehicle; and 6) we discuss the implications of these findings for the design of technology that supports work and wellbeing related activities in automated cars.

2. Related Work

2.1. Work in Cars

An emerging body of work in human-computer interaction explores the car as a workplace for knowledge workers (e.g. Chuang et al. (2018), Sadeghian Borojeni et al. (2019), Kun et al. (2019), Schartmüller et al. (2020), Laurier (2004), Eost and Flyte (1998)). A number of researchers have investigated driver engagement in work and entertainment tasks in manually-driven vehicles (for a recent overview see (Kun, 2018)). For example, Eost and Flyte (1998) used case studies and commuting diaries and found that people experience several ergonomic challenges when in the car, such as lack of space/storage and poor communication facilities. Alt et al. (2010) proposed a system for consuming entertainment content in small chunks as drivers wait at a traffic light. Their work shows the opportunity to use short time-chunks for non-driving related activities when drivers do not have to pay attention to the road. Martelaro et al. (2019) explored two productivity tasks that are intimately familiar to knowledge workers: creating slides and writing documents. In a simulator study, they found that participants are able to complete such tasks using a speech interface and drive safely in simple driving scenarios. The authors argue that decomposing larger tasks (such as creating a slide presentation) into smaller tasks (such as identifying the title of one slide) can allow work-related tasks to be completed in the driving environment. The idea is that the small tasks, or microtasks, can be accomplished in a manner that leaves sufficient manual, visual, and mental resources for safe driving. Stevens et al. (2019) argue that automated vehicles with the appropriate arrangement of space within the cockpit will allow for both work and relaxation during the drive.

Working in manually-driven vehicles has also been explored for police officers. These workers drive while operating devices such as the police lights and siren, as well as conduct knowledge work such as queries of remote databases, either accessing them directly or by talking to a remote conversant (the dispatcher). Miller and Kun (2013) examined logs from about 200 police vehicles collected over three years. The vehicles were equipped with a system that allowed officers to complete non-driving tasks using speech commands, a GUI, or original interfaces provided by device manufacturers (e.g. levers to turn lights on and off). The authors found that speech input was used most often for remote database queries. This is a task that, without a speech interface, requires extended manual-visual interaction with a GUI and keyboard, and also requires mental processing of data. Clearly, when driving, it is usually safer to issue voice commands to a computer than it is to look at a GUI and type (c.f. Medenica and Kun (2007)). Short tasks, such as turning police lights on or off, were accomplished manually. This finding underscores the importance of designing interfaces that take into account the manual, visual, and mental resources needed to complete the non-driving task, as well as the driving task (Wickens, 2002). Researchers have begun to explore technologies for supporting non-driving related tasks in highly automated vehicles, for example by investigating the use of mixed-reality interfaces (Riegler et al., 2020a,b, Becerra et al., 2020).

However, as we work towards supporting engagement in non-driving tasks in automated vehicles, we need to understand how these non-driving tasks fit into the broader context of the lived experience of drivers.

Existing work in the form of surveys, observation and interviews, helps us understand the experience of commuters and how automated vehicles may effectively increase the propensity to multitask while in transit (Keseru and Macharis, 2018, Milakis et al., 2017). For example, Malokin et al. (2019) used a survey to measure travel multitasking attitudes and behaviors, and found that multitasking is significant to transportation mode choice. Their results indicate that in the long-term autonomous vehicles might capture travel multitaskers and increase the demand to "drive-alone" mode. Shaw et al. (2019) conducted a study of Northern California commuters for investigating the benefits and disadvantages of travel-based multitasking and found that conditions that facilitate multitasking benefits (such as getting work done) might simultaneously result in disadvantages (such as increased stress). Pfleging et al. (2016) applied mixed methods to identify a broad set of non-driving activities for future automated vehicles that are of interest to commuters, from those that help them relax to those that keep them productive. Other researchers applied methods such as co-design to explore how future automated vehicles can positively affect the way we use our time (Stevens et al. (2019)). Hecht et al. (2020) conducted a driving simulator experiment to explore which non-driving tasks would be of interest to users of automated vehicles. Each of these approaches has strengths–surveys bring information from a large group of participants; co-design helps researchers gain deeper understanding of the reasons for user preferences; and controlled driving simulators studies can provide insight into the effects of context on participant behaviors.

The study we present here extends the existing work on working in cars and on multitasking-while-commuting by investigating in a high level of detail the activities of *drivers* rather than passengers or transit-riders. In this study we employed a novel time-use questionnaire. We will introduce time-use studies shortly, but first we will discuss levels of vehicle automation as well as the interaction between non-driving tasks and driving.

2.2. Levels of vehicle automation

The exploration of in-vehicle interfaces for automated vehicles is commonly conducted using the six levels of automation described by the SAE taxonomy (SAE J3016, 2016). In this taxonomy, level-0 indicates no automation, while level-1 and level-2 indicate that the vehicle provides assistance with one or two driving functions, respectively. The two driving functions covered by the taxonomy are maintaining lateral and longitudinal vehicle position (that is, steering, and acceleration-braking).

In vehicles with automation levels 0 through 2 the driver is in charge of driving at all times. Automation, if it is operational, is only an assistive function. As of 2021, all vehicles on the road have at most level-2 automation. A significant change will happen when level-3 automation is deployed. According to the SAE taxonomy, level-3 automation will allow drivers to completely disengage from driving for some period of time. They will still be responsible for returning to driving within a short amount of time (which is not specified in the taxonomy), upon request from the automation. Vehicles with automation levels 4 and 5 will transport passengers without requiring them to drive at all, with level-4 vehicles being constrained to only some contexts (e.g, geographically), while level-5 vehicles being fully autonomous.

In the context of the SAE taxonomy, our work focuses on understanding current behaviors in vehicles with automation levels 0, 1, and 2, in order to help us better design user interfaces for future vehicles with level-3 automation.

2.3. Impact of Non-Driving (Secondary) Tasks on Driving

The promise of level-3 vehicle automation is that the driver can engage in non-driving tasks. However, when automation issues a request that the driver take back control, the driver must be able to do so safely and in a timely manner. The ability of the driver to respond to a request to take back control will depend on the non-driving task that they engage in. Non-driving tasks might require visual attention and cognitive effort by the driver, as well as manual manipulation of different interfaces. The more visual, cognitive and manual effort a task requires, the more likely it is that the driver will find it difficult to quickly stop the task and safely return to driving. Wickens elegantly described this idea through his multiple resource theory. Wickens argues that humans have multiple resources to handle perception, cognition and responding (Wickens, 2002). When two task compete for the same resources, performance on both tasks can suffer. In our case, if a non-driving task requires visual and manual resources, it is competing for the same resources that are needed to resume driving, and this can be a safety issue.

Of course, ideally, when the automation issues the request for the driver to take back control, the driver would do so immediately, and there would be no competition for resources. However, we cannot expect drivers to switch between non-driving and driving tasks instantaneously (Janssen et al., 2019). Instead, drivers will likely go through an interleaving stage, during which they will switch back and forth between the two tasks Nagaraju et al. (2021). Only after this interleaving stage can we expect drivers to be fully engaged in the driving task. Note that we can expect that drivers will often be interrupted in their non-driving tasks and will have to return to the driving task relatively quickly (Janssen et al., 2019).

All of this means that we have to be careful in how we design interfaces for non-driving tasks in automated vehicles. For example, if a driver is typing on a laptop when automation is in charge, they are using their visual attention, cognitive resources, and hands to complete this task. When automation issues a request for the driver to take back control, the driver will now need these resources to first stow the laptop, and then visually orient themselves to the driving task and finally take back physical control of the vehicle. Furthermore, the driver will likely interleave the two tasks for a period of time, as they attempt to find a convenient break-point for the non-driving task, perhaps so as to make it easier to resume the task at a later point (cf. (Iqbal et al., 2005, Kun et al., 2013)). With this in mind, it is not surprising that Merat et al. found that engagement in a secondary task during automated driving can negatively affect subsequent manual driving performance

(Merat et al., 2012). This is a critical point: we cannot simply design in-vehicle interfaces that allow drivers to engage in non-driving tasks while automation is in control. We must also understand how engagement in the non-driving tasks will affect the driver *after* those tasks have been completed, or suspended, and the driver is in control of the vehicle.

Our work provides new safety-related insights, by providing a detailed analysis of non-driving tasks that drivers are likely to engage in (both in current vehicles, and in future automated vehicles), and by identifying the resources that drivers need for these tasks.

2.4. Time-use Studies

How individuals allocate their time has been a topic of interest in economic research for decades (Becker, 1965, Heckman, 2015). The increasing availability of data on time allocation choices in the household (Kostyniuk and Kitamura, 1982), and more broadly across other personal and work activities, has led to a breadth in empirical research on the topic (Kitamura et al., 1996) and to a broader understanding of the implications of different time-related behaviors (Gershuny and Fisher, 2013). The American Time-Use Survey (ATUS) (United States Bureau of Labor Statistics, 2018) is one of the primary sources of data in the domain of empirical time use studies. The survey provides insight on differences in work and leisure habits across different parts of the populations and across different stages of the economic cycle (Aguiar et al., 2013). The data also allows researchers to study the relationship between different time use allocations and wellbeing outcomes (Krueger et al., 2009, Krueger, 2009). Researchers also built further evidence on this topic using the survey-based Day Reconstruction Method (DRM), in which participants are asked to fill in a diary about the previous day, including their personal emotions related to each specific activity (Kahneman et al., 2004). This approach allowed researchers to reconstruct an individual's time allocation and emotions during each activity, and the relationship between well being and time use. More recently, time use studies have been used to explore differences in behavior across large samples of CEOs (Bandiera et al., 2016). Our study expands on the existing literature, by providing new insights on the commuting activities of knowledge workers.

Time-use studies provide researchers both a way to estimate the time-share of a particular task during the given time period, but also the order in which the participant engaged in different tasks, and if they engaged in multiple tasks at the same time. Thus, time-use studies can provide insight into both the prevalence of a task, as well as how it is related to other tasks.

The other reason for deploying a time-use study is that we need to understand the temporal relationship between the different tasks undertaken in the car, and also between tasks in the car and those before and after the drive. Understanding these temporal relationships can help us design tools that can tie these activities together for improved productivity and wellbeing. Furthermore, information about the temporal relationship between in-vehicle non-driving tasks can help us build interfaces that will support safe driving, particularly for the situation when automation instructs the driver to take back control.

3. Study of Commuting by Driving Knowledge Workers

3.1. Goal and Research Questions

The goal of this study is to understand how future automated vehicles can support the work and wellbeing of knowledge workers.To pursue this goal, we need to gather evidence on two broad issues. First, we need to understand how commuting currently fits into the workday of knowledge workers, and whether and how knowledge workers engage in multitasking-while-driving behavior when driving to/from work–that is, do they drive and engage in non-driving tasks at the same time? Second, we need to gather information on the activities that knowledge workers see themselves engaging in while commuting in a future safe highly-automated vehicle (AV).

More specifically, we aim to examine the following research questions:

Q1. How does commuting relate to the typical daily time allocation of knowledge workers and to their general life satisfaction?

Q2. What work and personal activities do knowledge workers currently engage in while commuting? What are the perceptual, response, and cognitive demands of the secondary (non-driving) tasks involved?

Q3. To what extent do knowledge workers multi-task while driving to/from work? When does multitasking occur?

Q4. How does commuting relate to other activities during the day?

Q5. What do knowledge workers expect to do when commuting with a future safe Autonomous Vehicle (AV)? What work and personal activities would knowledge workers like to engage with when commuting in an AV?

To pursue these questions we conducted an online time-use study of knowledge workers, which we describe in detail below.

3.2. Methods

3.2.1. Participants

We recruited participants from the United States (U.S.), using the online paid marketplace platform Lucid,[1] which partners with several companies to recruit individuals to answer online surveys. Lucid received $13.00 per complete response and the research team did not have control over how much of this value is transferred towards survey participants. Participants could receive either direct financial compensation or indirect compensation (e.g. "fidelity" points similar to credit card points that are redeemable by products). In total, we collected data about individuals recruited from 29 different companies, all of which are third-party companies that have access to panels of workers and their respective contact information. [2] To recruit participants, Lucid and their partnering companies only had access to the survey description that we provided them. Being cognizant that if potential participants knew the research team would evaluate commuting behavior, multitasking while driving, or preferences related to autonomous vehicles, this could bias our sample and responses, the survey was always advertised as a study "to understand time use, and how that affects productivity and well-being."

Potential participants were screened for the following criteria: 1) employed in a full-time job (+35 hours/week); 2) earning an annual salary income of at least $40,000 US dollars (which corresponds to approximately the 6th percentile of the income distribution of knowledge workers in the US); 3) working in an occupation classified as "knowledge worker" occupation."[3] Individuals meeting all the above criteria were invited to start the survey. In addition, we set quotas to create a sample of knowledge workers whose average socioeconomic characteristics matched the characteristics of knowledge workers described in the US Census' 2018 Current Population Survey (United States Census Bureau, 2018)).

In total, 616 knowledge workers responded to our survey, of which 493 (80%)

[1]https://luc.id/marketplace/

[2]Each company used their internal policies to contact potential participants and to provide incentives (e.g. a company might contact participants via email or applications, and provide gift cards, virtual currency, charitable donations, and/or cash transfers).

[3]Individuals self-reported their occupation's title using the US Standard Occupational Classification (SOC). The SOC classifies occupations on the basis of their association with high cognitive versus high manual workload and/or a high degree of adaptation versus repetitiveness, and leads to four occupational groups: non-routine cognitive, non-routine manual, routine cognitive, and routine manual (Foote and Ryan, 2014, Parker and Woodford, 2015). Following the economic literature on occupational tasks (Autor et al., 2003), we considered an an individual to be a knowledge worker if their occupation fell under the non-routine cognitive occupational group.

were commuters (i.e. reported at least one commuting event in the time-use diary) and 123 (20%) were non-commuters. Within the sample of commuters, 400 (81.1% of commuters, 64.9% of all respondents) reported at least one commuting event in which they were driving. Our analysis focuses on this sub-sample of 400 individuals who drive themselves to/from work. Table 1 reports the descriptive statistics of our sample. Table 1 shows that the sample broadly matches the empirical distribution of knowledge workers surveyed by the U.S. Census in the 2018 Current Population Survey.

	2018 US CPS (N=557,925)	All respondents (N=616)	Non-commuters (N=123)	Commuters (N=493)	Commuters who drive a car (N=400)
Socioeconomic variables					
Gender					
Female	47.9%	49.2%	35.8%	52.5%	51.5%
Male	52.1%	50.8%	64.2%	47.5%	48.5%
Annual salary (in USD)					
$39.999 or lower	5.9%	-	-	-	-
$40,000 to $59,999	21.6%	19.8%	14.6%	21.1%	20.5%
$60,000 to $79,999	31.1%	25.6%	17.1%	27.8%	27.5%
$80,000 to $99,999	23.4%	19.2%	25.2%	17.6%	18.7%
$100,000 or higher	18.1%	**35.4%**	43.1%	33.5%	33.3%
Highest education degree					
Less than a college degree	20.9%	13.6%	13.0%	13.8%	15.7%
College degree	48.3%	49.4%	45.5%	50.3%	50.5%
Graduate degree	30.8%	37.0%	41.5%	35.9%	33.8%
City/Distance characteristics					
City size (home)					
Large Metropolitan Area	*	57.0%	61.8%	55.8%	50%
Metropolitan Area	*	18.7%	14.6%	19.7%	21.7%
Medium-sized Urban Area	*	9.7%	11.4%	9.3%	10.3%
Small-sized Urban Area	*	4.9%	4.1%	5.1%	6%
Rural Area	*	9.7%	8.1%	10.1%	12%

Table 1: Sample of US knowledge workers: main characteristics. Note that city size bins in the US Current Population Survey (CPS) do not match the ones used by our research team in the survey.

3.2.2. Procedure

After completing the screening questionnaire, participants were redirected to an online consent form. Upon consenting, they were redirected to the time-use survey. The entire survey (screening, consent form, and time-use survey) were hosted in *Qualtrics*.

3.2.3. Survey

We designed a new time use survey adapted from the Daily Reconstruction Method survey (Kahneman et al., 2004). First, participants were prompted to recall a "representative" working day from the previous week, and asked to mark which day of the week it was, and at what times they woke up and went to sleep. Then, we asked participants to fill in a time-use diary with information about activities they engaged in during that day. For each activity, participants had to select an activity title from a list of 22 activities as well as the start and end time of the activity. The time-use diary had three different sections, one for each part of the day (morning, afternoon, and evening). In each section, participants entered between 1 and 10 activities that started in that time period. Thus, each participant reported up to 30 activities in their diary.

We asked participant to report on activities that met at least one of the following criteria:

1. Any activity that lasted at least 15 minutes; and
2. Any activity that involved commuting/travelling to and from work; and/or
3. Any activity that the participants felt was particularly important in their daily routine.

To help participants recollect the activities undertaken on that representative working day, we encouraged participants to enter personal notes in a free text field in the survey. This field was optional and intended to assist participants to recollect their day. We notified participants that the research team would delete this information as soon as the survey ended. Participants could also add free text subtitles to each activity. Figure 1 shows a screenshot from the morning section of the diary.

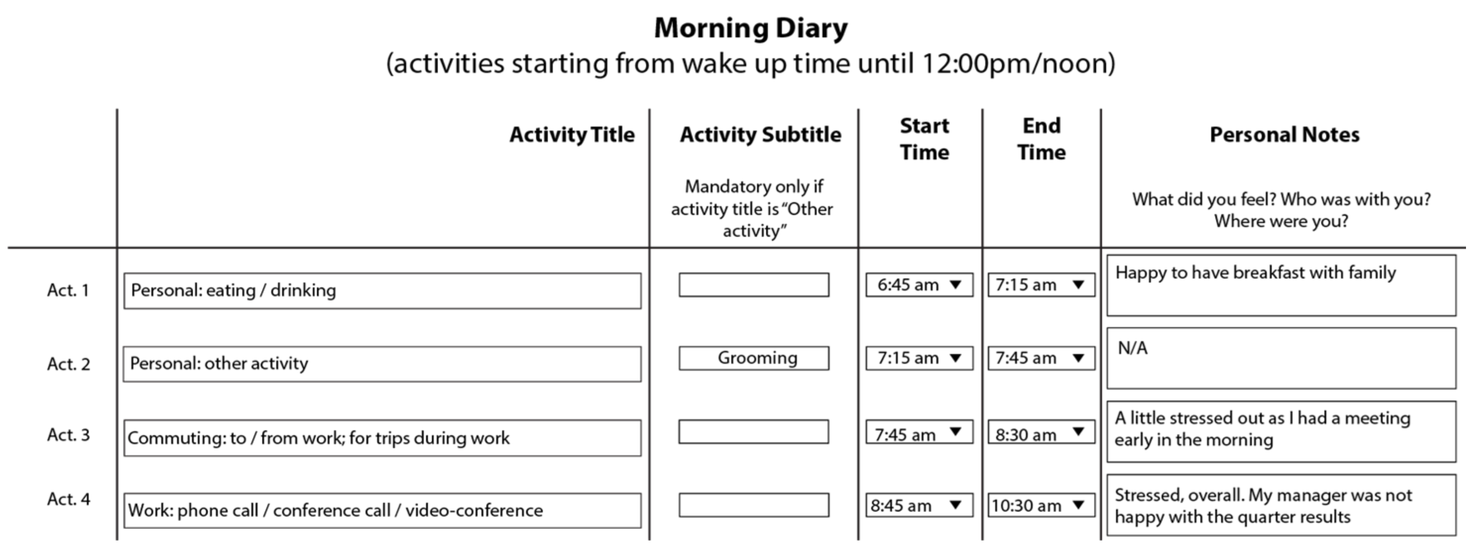

Figure 1: Screenshot of the Morning Section of the Time-Use Diary

Next, the time-use diary asked for details about each commuting event the participant marked in the time-use diary. For each commuting event, we asked participants about the modality of transportation, the presence of additional individuals, wellbeing while commuting,[4] and which secondary activities participants undertook during that commuting event (multitasking).

Secondary tasks are defined as any activity that the participant engaged in simultaneously with the act of commuting. Secondary activities were selected from a list of 30 options that included 17 work-related and 13 personal secondary activities. We classified activities based on their (non-exclusive) visual, auditory, manual, and speech demands. For instance, writing/editing documents have both visual and manual requirements, listening to podcasts present mostly an auditory demand. Although all secondary activities implied some cognitive demand, the subset of activities that required only mental effort–such as planning and reflecting–were classified as a separate category. This classification allows us to categorize the resource requirements arising when multitasking while commuting.

Finally, participants were asked to select one out of the 30 secondary activities that they were most likely to engage in when commuting in a future safe autonomous vehicle. We asked this question separately for the morning and afternoon/evening commute. In the appendix, we add a list of all the potential primary and secondary activities participants could select from.

The study concluded with questions about demographics and workplace characteristics, and a Cantril-measure of overall life satisfaction measured on an 11-point scale (OECD, 2013).

3.2.4. Data Analysis

We now proceed to describe the results emerging from the data in three steps.

First, we report results on how time spent commuting correlates with work-related or personal time, and with one's perception about overall life satisfaction. The main dependent variables are the total daily time (in minutes) reported in work-related activities and (separately) in personal-related activities. We also use

[4]wellbeing while commuting was assessed using the method employed in the 2012 and 2013 ATUS wellbeing module to event-level wellbeing (Council, National Research, 2012). For each commuting event, participants are asked to answer how strongly they felt these six emotions: happiness and meaningfulness ("positive" emotions), tiredness, sadness, pain, and stress ("negative: emotions). participants scored each emotion using a 7-point scale where 0 represent not feeling that emotion and 6 represent feeling it strongly.

the self-reported measure of life-satisfaction (0-10 score) to capture how satisfied a worker is with their life.

We report the results from three multiple ordinary least squares (OLS) regression models. In the first two models, we estimate the conditional correlation between daily time allocated to work-related activities and time allocated to personal activities (aside from sleeping), respectively, and daily time reported commuting. Both models are estimated using a log-log specification.[5] In the third model, we replace the dependent variable by the self-reported Cantril-measure of life-satisfaction. In all regressions models we add control variables related with respondents' socioeconomic characteristics (gender, educational background, salary, whether an individual is older than 40 years old, whether and individual has children, and with how many people the respondents lives with), work characteristics (log of years employed in the firm, log of years in the current position, industry, whether the individual is a manager, and log of firm size), and commuting characteristics (size of city of residence, size of city where the individual works, and whether the individual lives further than 6 miles away from work, all these variables measured as categorical variables). We also add control variables to account for differences in how well respondents answered the time-use diary (e.g. log of total-time reported in the time-use diary, total time in the survey, and day-of-week portrayed in the time-use diary). Estimated standard errors are White-Huber errors robust to heteroskedasticity and we report statistical significance using a two-tailed student-t test.

Second, we analyze whether and how knowledge workers engage in multitasking during the commute, in work or personal-related activities. We use all commuting events reported by participants in their time-use diaries to: (1) analyze the frequency of commuting events involving work-related and/or personal secondary activities while driving; (2) analyze the frequency of commuting events involving multiple secondary activities while driving; (3) report the detailed types of secondary activities engaged in when commuting, as well as the resource demands of these activities. We further compare how morning and evening commuting events differ in terms of frequency of work-related and personal activities; and (4) report whether knowledge workers use commuting to either anticipate/continue activities

[5]We regress the natural logarithm of time spent in work-related (or personal) activities against the natural logarithm of time spent commuting to facilitate the interpretation of the estimated regression coefficients. In this specification, the coefficient represents an approximation of the percentage point increase in work-related (or personal) time associated with a one percent increase in time spent commuting.

engaged outside car. We report statistical significance on the differences between morning and evening commutes using a Pearson's chi-squared test for equality of frequencies.

Finally, the last stage of our analysis examines what secondary activities respondents would choose to engage with when commuting using a future safe autonomous vehicle. We compare the share of respondents expecting to engage in each one of the 30 types of secondary activities.

We used StataCorp's Stata software, version 16, to conduct all quantitative analyses.

4. Results

In this section we summarize the results for the 400 knowledge workers in our sample who drive themselves to and from work. Within this sample, 373 workers reported information about their morning commute and 298 reported information about their afternoon/evening commute.

4.1. Time-Diaries

The 400 commuters in our sample who drive, entered an average of 14.1 daily activities (SD = 6.7). This is similar to the mean of 14.1 activities per day (SD = 4.8) in the original DRM study (Kahneman et al., 2004). Considering the full range of 1440 minutes (24 hours) in the day and attributing the time before participants woke up and after they went to bed as personal time, the average time diary in our sample covers 1211.6 minutes (20.4 hours) of a respondents' day (SD=187.0 min. or 3.1 hours). Furthermore, considering only the time between participants waking up and going to bed, the average time diary in our sample reports activities that added up to 791.5 minutes (13.2 hours) per day (SD=196.8 min. or 3.3 hours). Each activity lasted an average of 56.3 minutes (SD = 55.1 minutes). Participants mainly reported their activities for Mondays (46%), Tuesdays (23.3%), and Wednesdays (21.3%).

Our 400 knowledge workers, on average, allocated 5.9% of their daily time to commuting (SD = 4.6%), 33.0% to work-related (SD = 9.8%), and 61.0% to personal activities (SD = 9.9%). These statistics consider all time reported by participants and the time participants spent sleeping (before waking up and after going to bed). The average participant reported spending a total of 71.8 minutes/day on commuting activities (1.2 hours/day, SD =54.8 minutes/day), 405.7 minutes/day working (6.8 hours/day, SD=138.6 minutes/day), and 734.1 minutes/day on personal activities, including sleeping (12.2 hours/day, SD = 136.8 minutes/day).

Excluding the time before waking up in the morning and going to bed in the evening, the average participant reported 314.0 minutes/day on personal activities (5.2 hours/day, SD=143.7 minutes/day).

Figure 2 summarizes how the sample of 400 knowledge workers, who commute by driving, allocated their time across commuting, work-related, and personal activities. This figure provides a validation that our data also have patterns that are similar to the ones reported in the American Time Use Survey (ATUS) (United States Bureau of Labor Statistics, 2018), namely, that workers commute between 6AM and 9AM in the morning and later commute between 4PM and 6:30PM in the evening (both instances represented by thicker orange areas in the time-use map).

4.2. Commuting, Personal Time and Life Satisfaction

Commuting time mainly crowds out personal time: commuting time is negatively associated with time spent in personal activities. A 1% increase in daily commuting time is associated with an approximate 0.357% decrease of daily personal time (excluding sleep) (two-tailed t-test(360) = -3.31, $p \leq 0.01$). In contrast, a 1% increase in commuting time is associated with an approximate 0.1% decrease in work-related time (two-tailed t-test(360)=-1.65, $p \leq 0.1$). We report the table with the regression results in the appendix.

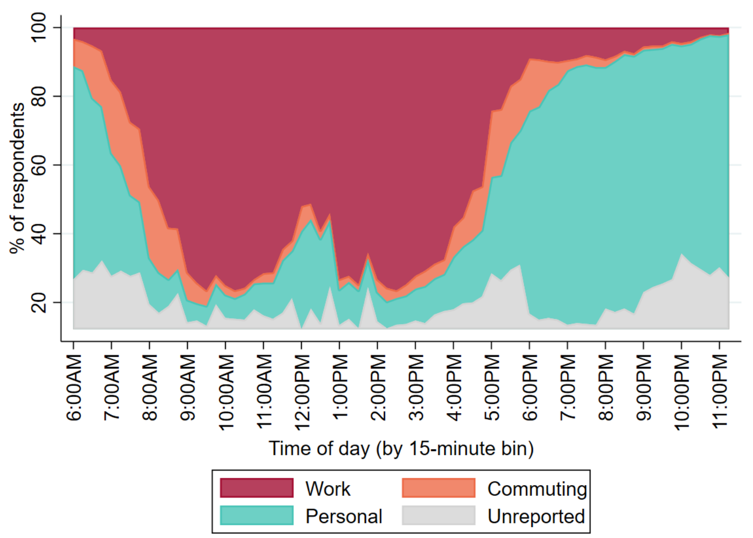

Figure 2: Time-Use of 400 knowledge workers who commute by driving a car. Each colored area shows the percentage of knowledge workers engaging each respective type of activity by every 15-minute window in the time-use diary. All time windows before the respondent woke up and after the respondent went to bed are classified as personal time.

Commuting time is also negatively correlated with overall life-satisfaction, even controlling for a host of participant characteristics. A 1% increase in commuting time is associated with an approximate reduction in the perception of overall life wellbeing by 0.30 points on the 11-point Likert-scale wellbeing score. Such magnitude is equivalent to 4.1% of the average wellbeing score (average = 7.3, SD = 1.8). This conditional correlation is significant at the 5% significance level (two-tailed t-test(359)=-2.10, $p \leq 0.05$) and is consistent with the findings of prior empirical work (Hilbrecht et al., 2014, Stutzer and Frey, 2008, Kahneman et al., 2004).

4.3. Multitasking Behavior while Driving to and from Work

We analyzed the extent to which participants engaged in non-driving (secondary) activities across 671 driving commuting events (373 in the morning and 298 in the afternoon/evening). Respondents report engaging in at least one secondary activity in 87.0% of all commuting events. Morning commuting activities were only 4.4 minutes shorter than evening commuting activities (student t-test(d.f. = 669) = 2.294, $p \leq 0.05$) and there was no difference between engagement in secondary activities during the morning (88.2%) and evening (85.6%) commutes (Pearson's chi-squared = 1.018, $p \leq 0.313$).

We now provide a more detailed characterization of these secondary activities occurring during the commute.

First, in terms of *timing* when these secondary activities occur, the data show that work activities are more likely to occur during the morning vs. the evening commute: 43.7% of reported morning commutes involved some form of work while driving vs. only 31.2% of reported afternoon/evening commutes (a difference of 12.4 percentage points, Peason's chi-squared = 10.954, $p \leq 0.01$). We find no difference between the morning and evening commute for the probability of engaging in a secondary personal activity: participants reported engaging in a secondary personal activity while driving in 57.4% and 61.7% of the morning and afternoon/evening commutes, respectively, and the difference is not statistically different from zero (Pearson's chi-squared test = 1.132, $p \leq 0.252$).

Second, in terms of the *number* of non-driving secondary tasks that commuters undertake while driving to/from work, 51.6% of commuting events involved a single secondary activity, 35.5% involved two or more secondary activities, and the remaining 12.9% involved no secondary activity. Figure 3 shows the share of morning and afternoon/evening commuting events by the number of secondary tasks if we considered only secondary work-related activities (left-panel) or only secondary personal activities (right-panel). This figure indicates that the main difference between morning and afternoon/evening commute in terms of intensity of multitasking behaviors is in the probability of engaging in two or more secondary work-related activities (+10.1 percentage points more likely in the morning commute, Pearson's chi-squared test for equality of frequencies when comparing morning and evening commute = 13.409, $p \leq 0.01$). There is no statistical difference in the number of *personal-related* secondary activities across morning and afternoon/evening commutes (Pearson's chi-squared test = 1.417, $p \leq 0.492$).

Third, we show the *type* of secondary activities workers engage with during the commute, in Table 2. Out of all work-related activities, reading emails is most frequently reported (17.9% of all commuting events) and with the largest difference between morning and afternoon/evening commutes (8.0 percentage points more likely in the morning commute, Pearson's chi-squared = 7.264, $p \leq 0.01$). Although there is variability in how frequently the different work-related activities are reported (e.g. only 2.8% of the commutes include in-person meetings, while 8.9% include some form of non-email work-related reading), all work-related activities are more likely to occur in the morning rather than in the evening commute (with the exception of "other," but this activity is reported in less than 2% of all commutes, and the difference between morning and afternoon/evening is negligible). Listening to music is the only personal activity that varies across morning vs. afternoon/evening commutes (it is 9.2 percentage points less likely to occur in the morning, Pearson's chi-squared = 6.219, $p \leq 0.05$).

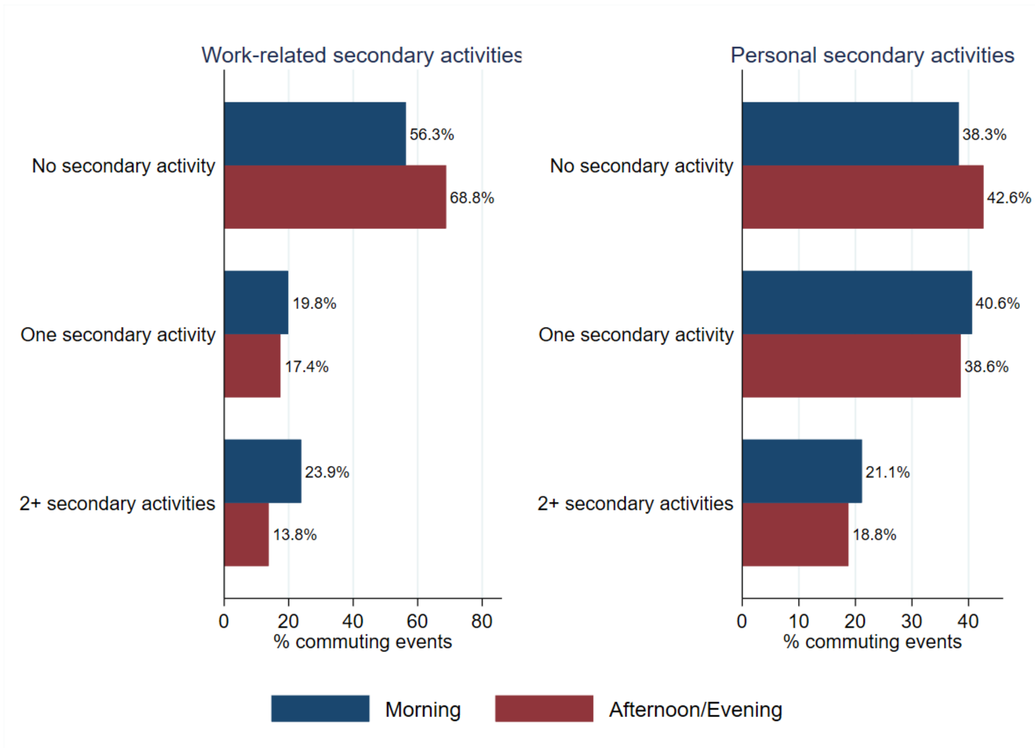

Figure 3: Share of commuting events by intensity of work-related multitasking behavior. Each panel considers only instances of secondary activities associated to each respective type of activity (work or personal, respectively). Since participants were able to report multiple secondary activities in each commuting event, the sum of the share of events with work-related activities and the share of events with personal activities adds up to more than 100%.

	% of commuting events	% of commuting events within period of day		Morning vs. Afternoon/Evening		
		Morning	Afternoon / Evening	Difference (percentage points - p.p.)	Pearson’s Chi-squared	p-value
No secondary activity	12.9%	11.8%	14.4%	-2.6p.p.	1.018	.313
W: reading emails (V, M)	17.9%	21.4%	13.4%	8.0p.p.	7.264	.007**
W: replying emails (V, M)	9.5%	11.8%	6.7%	5.1p.p.	4.964	.026*
W: reading (V)	8.9%	11.3%	6.0%	5.2p.p.	5.543	.019*
W: phone call (with one person) (S, A)	7.5%	8.6%	6.0%	2.5p.p.	1.548	.213
W: thinking/reflecting (CO)	7.0%	7.2%	6.7%	0.5p.p.	.071	.79
W: planning (CO)	6.9%	8.6%	4.7%	3.9p.p.	3.908	.048*
W: making a to-do list (CO)	6.6%	7.2%	5.7%	1.5p.p.	.636	.425
W: analyzing (V)	6.4%	8.0%	4.4%	3.7p.p.	3.741	.053
W: browsing/social media/messaging (V, M)	5.7%	6.2%	5.0%	1.1p.p.	.398	.528
W: listening to podcast/audio book/lecture (A)	5.7%	7.8%	3.0%	4.8p.p.	7.01	.008**
W: preparing (V, M)	5.4%	7.0%	3.4%	3.6p.p.	4.263	.03*
W: conference call (with two people or more) (S, A)	4.8%	5.9%	3.4%	2.5p.p.	2.358	.125
W: programming (V, M)	3.9%	4.6%	3.0%	1.5p.p.	1.051	.305
W: video-conference (V, S, A)	3.7%	5.6%	1.3%	4.3p.p.	8.49	.004**
W: writing/editing (V, M)	3.3%	4.6%	1.7%	2.9p.p.	4.332	.037*
W: in-person meeting (V, S, A)	2.8%	3.5%	2.0%	1.5p.p.	1.304	.253
W: other activity (NA)	0.6%	0.5%	0.7%	-0.1p.p.	.051	.821

Table 2: Detailed breakdown of commuting events by type of secondary activities. Since participants were able to report multiple secondary activities in each commuting event, the sum of the share of events with work-related activities and the share of events with personal activities adds up to more than 100%. Work-related activities are marked with "W" and personal activities are marked with "P". Resource demands are the following: Visual (V), Manual (M), Speech (S), Auditory (A), Cognitive Only (CO). We classified "making a to-do-list" as a cognitive only activity as it does not necessarily entail writing activities. Significance levels of Person’s Chi-squared test: **p-value<0.01, *p-value <0.05.

	% of commuting events	% of commuting events within period of day		Morning vs. Afternoon/Evening		
		Morning	Afternoon / Evening	Difference (percentage points - p.p.)	Pearson's Chi-squared	p-value
P: listening to music/radio (A)	33.8%	29.8%	38.9%	-9.2p.p.	6.219	.013*
P: thinking/reflecting (CO)	16.8%	14.7%	19.5%	-4.7p.p.	2.633	.105
P: phone call (S, A)	9.7%	9.7%	9.7%	-0.1p.p.	.001	.972
P: listening to podcast/audio book (A)	9.2%	8.8%	9.7%	-0.9p.p.	.154	.694
P: browsing/social media/messaging (V, M)	4.9%	5.4%	4.4%	1.0p.p.	.354	.552
P: making a to-do list (CO)	4.2%	3.5%	5.0%	-1.5p.p.	.993	.319
P: praying/mediating/worshiping (CO)	3.9%	4.0%	3.7%	0.3p.p.	.048	.826
P: relaxing/resting/sleeping (CO)	3.7%	4.6%	2.7%	1.9p.p.	1.62	.203
P: reading/replying email (V, M)	3.7%	4.0%	3.4%	0.7p.p.	.205	.651
P: watching videos/tv (V)	3.1%	3.5%	2.7%	0.8p.p.	.35	.554
P: reading (V)	3.0%	3.2%	2.7%	0.5p.p.	.162	.687
P: exercising (V, M)	1.6%	1.9%	1.3%	0.5p.p.	.293	.588
P: other activity (NA)	1.5%	1.6%	1.3%	0.3p.p.	.08	.777

Table 2 (continued): Detailed breakdown of commuting events by type of secondary activities. Since participants were able to report multiple secondary activities in each commuting event, the sum of the share of events with work-related activities and the share of events with personal activities adds up to more than 100%. Work-related activities are marked with "W" and personal activities are marked with "P". Resource demands are the following: Visual (V), Manual (M), Speech (S), Auditory (A), Cognitive Only (CO). We classified "making a to-do-list" as a cognitive only activity as it does not necessarily entail writing activities. Significance levels of Person's Chi-squared test: **p-value<0.01, *p-value <0.05.

4.3.1. Resource Demands

We explore the detailed breakdown of activities to study how resource demands vary across multitasking activities. We use the four-dimensional multiple resource model proposed by Wickens (2002), and we classify each activity according to its visual, auditory, manual, speech, and cognitive-only demands. Visual and auditory demands are related to perception. Manual and speech demands are related to responses and actions by the participant. Cognitive-only demands are related to tasks that are dominated by thoughts, and require little or no perception or action/responding. In the perception and cognition stage of Wickens' model we ignore the difference between spatial and verbal codes. Similarly, we ignore the difference between focal and ambient vision for visual processing. We do this because we focus on the salient elements of in-vehicle activities, which are the perception modality (visual or auditory), the type of response (manual or speech), and cognitive-only activities.

Auditory and cognitive only demands were similar across morning vs. evening / afternoon commutes (auditory: 55.7% vs. 57.7%; cognitive only: 34.8% vs. 32.5%). However, a greater fraction of morning events had some form of multitasking with visual or manual demands (visual: 37.8% vs. 28.2%; manual: 32.7% vs. 24.8%). These patterns are shown in detail in Figure 4, which focuses on resource requirements across work-related and personal secondary activities. On average, work-related multitasking is more demanding in the morning across all resources. We used Pearson's chi-squared test to evaluate if there are differences in the demand for perceptual, response, and cognitive-only resources during the morning and evening commutes. We found that indeed there is more demand in the morning for visual perception (Pearson chi-squared = 10.133 / $p \leq 0.01$), auditory perception (Pearson chi-squared = 8.717 / $p \leq 0.01$), manual responding (Pearson chi-squared = 8.687 / $p \leq 0.01$), and speech responding (Pearson chi-squared = 5.462 / $p \leq 0.05$). There was no difference for cognitive-only tasks (2.495 / $p \leq 0.114$).

Figure 4 also shows that the morning and evening commute are similar in terms of the resource demands imposed by personal secondary activities. The only statistical difference is that evening commutes are +8.5 percentage points more likely to entail a secondary activity with an auditory demand (Pearson's chi-squared: 5.7634, $p \leq 0.016$). Further, personal activities are a lesser source of visual and/or manual demands in both morning (11.5% and 9.4%, respectively) and evening (8.7% and 7.4%, respectively) commutes, when compared to work-related activities. When taken together, these results imply that working while commuting, especially in the morning, is the main source of visual and manual distractions for drivers.

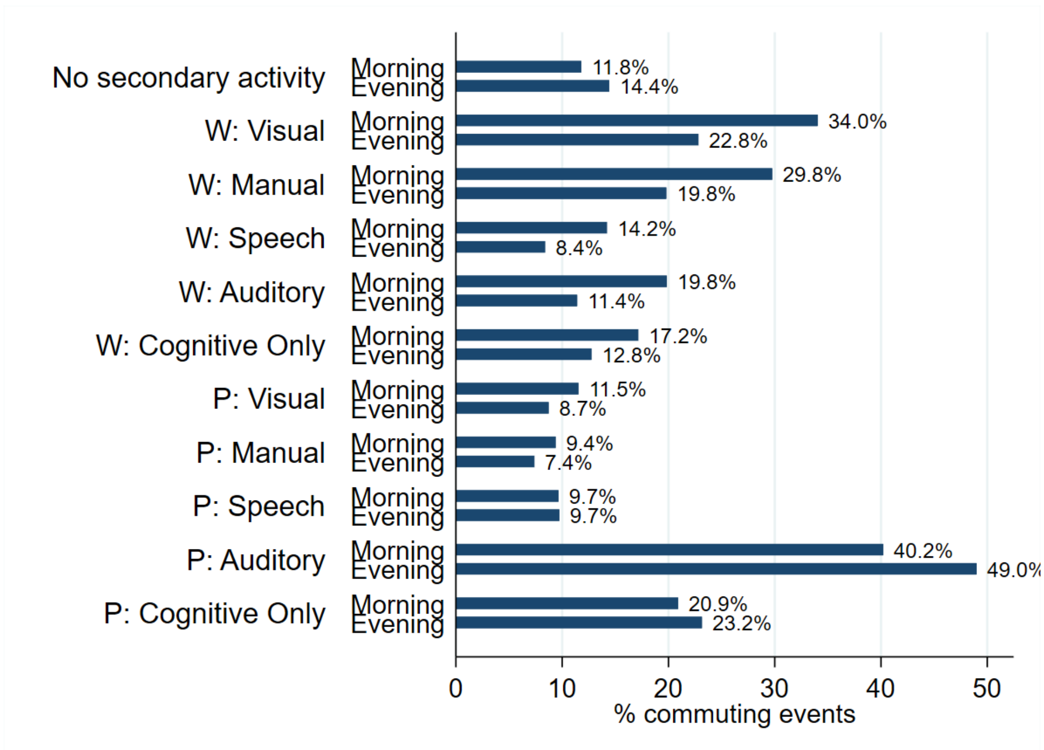

Figure 4: Detailed breakdown of multitasking while driving by resource demands. The bars within each period add up to more than 100% because: (1) participants were able to report multiple secondary activities in each commuting event, and (2) secondary activities may entail multiple resource demands. Work-related activities are marked with "W" and personal activities are marked with "P". Resource demands are the following: Visual (V), Manual (M), Speech (S), Auditory (A), Cognitive Only (CO).

4.4. Multitasking in the Car and Activities During the Day

We examined whether commuting is currently used as an opportunity for knowledge workers to anticipate or continue activities which take place outside of commuting, or whether it is a transition period, which is different from the activities that precede or follow the commute.

Results suggest that commuting separates personal from work-related activities. In the morning, 95% of the respondents report either personal or no activity before the morning commute, while 93% report engaging in work-related activities immediately after commuting in the morning. In the afternoon/evening, 85% of the respondents engage in work-related activities immediately before the commute and 79% engage in a personal activity following the commute.

Table 3 reports the main activities that respondents engaged in immediately after the morning commute (373 commuting events) and immediately before the afternoon/evening commute (298 commuting events). This table shows that the dominant first activity following the morning commute is reading/replying to emails (49%). In contrast, there is no such dominant activity preceding the afternoon/evening commute.

Our analysis also indicates that, currently, commuting is mostly a transition to/from work, rather than an anticipation/continuation of work. First, we find that 53% of knowledge workers who start working immediately after the morning commute do not engage in any work-related activity during their morning commute. Second, even when knowledge workers work during the commute, exact continuation of activities is rare: only 10% (5%) of morning commuting events involved the same secondary activity that was being performed as a main activity immediately before (after) the commute. Analogously, 15% (7%) of afternoon/evening commuting events involved the same activities that were performed immediately before (after) commuting. Third, 37% of respondents reported engaging in at least some secondary activity during the commute without engaging in the same activity as a main activity outside commuting. Taken together, these results indicate that knowledge workers' time allocation during commuting differs from time allocation during other periods of the day.

Activity	Immediately after morning commute (within 1h)	Immediately before afternoon/evening commute (within 1 h)
W: reading/replying emails	49%	12%
W: browsing/social media/alike	8%	4%
W: planning/preparing/thinking	12%	9%
W: writing/editing/programming	5%	14%
W: reading/analyzing	3%	13%
W: phone call and alike	4%	4%
W: in person meeting	7%	13%
W: leisure with colleagues/clients	2%	8%
W: other activity	3%	7%
P: sleeping	0%	1%
P: relaxing/resting	1%	2%
P: phone call	1%	0%
P: exercising	0%	2%
P: eating/drinking	1%	2%
P: other activity	0%	1%

Table 3: Detailed breakdown of activities conducted immediately after morning commute or before evening commute. This table only considers immediate activities that started within 1 hours after the morning commute or ended within 1 hour before the afternoon/evening commute. This table does not show activities that never immediately followed the morning commute or preceded the afternoon/evening commute.

4.5. *Expected Preferences for Secondary Activities in a Highly-Automated Vehicle*

Of the 373 (298) individuals that reported a commuting activity in the morning (afternoon/evening), 371 (296) answered the question about the secondary activity they would engage in while commuting had they had access to a highly-automated vehicle in that period.

Individuals exhibit a fairly consistent preference for engaging in work-related activities when commuting regardless of the type of vehicle they have: manually driven or highly automated. Thus, 74.1% of the individuals who reported engaging in some work-related activity during the morning commute would also engage in a work-related activity if they were commuting in a highly-automated vehicle (123 out of 166 individuals). Similarly, 75% of those who now report working in the afternoon/evening commute would do so in a highly-automated vehicle (72 out of 96).

To understand in more detail the expected changes in multitasking behavior while driving in an AV, we created an index to compare current and expected probabilities of each secondary activity while driving. First, within each commuting event and for each secondary activity, we computed a weight that receives value zero if the respondent did not engage in it, or 1/N if the respondent did engage in it, where N is the total number of secondary activities that the respondent engaged in during that commuting event. For instance, had a respondent engaged in one secondary activity, this activity would receive weight 1 and all others would receive weight zero. Had the respondent engaged in two secondary activities, each of these two activities would receive a weight of 1/2, and all others would receive weight zero, and so forth. Next, we average each activity's weight across all commuting events where any multitasking happened (590 commuting events). These indexes represent the probabilities of each respective activity happening in a commuting event in instances in which some multitasking while driving happened.

Second, we created an analogous set of indices using the preferences indicated in the highly-automated vehicle scenario. Since not all commuters entered both morning and afternoon/evening commutes in the time-use diary, we only use responses about the expected secondary activity in the morning and/or afternoon/evening commute for participants that reported a secondary activity in that respective commute. Further, as participants were asked to enter one activity for the morning commute and another activity for the afternoon/evening commute, we pooled morning and afternoon/evening responses and computed the share of each secondary activity across all these responses. This share represents the expected probability of each secondary activity while commuting in case participants had access to a highly-automated vehicle.

Table 4 shows the comparison between the weighted incidence of work-related and personal secondary activities that knowledge workers currently engage in to those secondary activities they would be most likely to engage in while commuting had they had access to a future safe highly-automated vehicle (the table combines morning and afternoon/evening commute). We see a wide variety of responses across different tasks.

Comparing the differences in such probabilities reinforces that demand for activities in a highly automated vehicle is dispersed across multiple activities. Aside from the activities "listening to music", "personal-related browsing/social media", "personal-related reading/replying to email", and "personal-related thinking/reflecting," which registered a -19.7 percentage points, a +8.8 percentage points, a +5.3 percentage points, and a -6.1 percentage points change in engagement probability, respectively, no other single activity was associated with a higher than +/-5 percentage-point variation in their probability of occurring in a highly automated vehicle.

Activity	Current incidence of secondary activity (weighted share of commuting events)	Expected incidence of secondary activity in AV (weighted share of responses)	Difference in expected versus current (percentage points)
W: reading emails	9.1%	10.7%	1.6%
W: replying emails	3.0%	6.3%	3.2%
W: browsing/social media/messaging	1.8%	4.1%	2.3%
W: programming	1.2%	3.7%	2.5%
W: planning	2.2%	3.4%	1.2%
W: analyzing	1.7%	2.5%	0.9%
W: reading	3.4%	2.4%	-1.0%
W: thinking/reflecting	3.2%	1.9%	-1.4%
W: preparing	1.4%	1.5%	0.1%
W: video-conference	0.6%	1.5%	1.0%
W: making a to-do list	2.2%	1.5%	-0.6%
W: conference call (with two people or more)	1.3%	1.2%	-0.1%
W: listening to podcast/audio book/lecture	2.1%	1.2%	-0.9%
W: writing/editing	0.7%	1.0%	0.3%
W: phone call (with one person)	2.8%	0.8%	-2.0%
W: in-person meeting	0.9%	0.8%	0.0%
W: other activity	1.7%	0.3%	-1.3%
P: browsing/social media/messaging	1.4%	10.2%	8.8%
P: listening to music/radio	27.9%	8.1%	-19.7%
P: reading/replying email	1.0%	6.3%	5.3%
P: relaxing/resting/sleeping	1.5%	5.9%	4.4%
P: watching videos/tv	1.0%	5.8%	4.8%
P: reading	0.8%	5.4%	4.6%
P: phone call	6.2%	3.7%	-2.5%
P: thinking/reflecting	9.8%	3.7%	-6.1%
P: listening to podcast/audio book	5.9%	1.9%	-4.0%
P: other activity	2.1%	1.7%	-0.4%
P: making a to-do list	1.2%	1.5%	0.3%
P: exercising	0.7%	0.5%	-0.2%
P: praying/mediating/worshiping	1.3%	0.3%	-0.9%

Table 4: Detailed breakdown of current weighted incidence of activities conducted while commuting and expected weighted incidence of activities conducted while commuting when using an Autonomous Vehicle.

We then evaluated the differences in such probabilities aggregating activities according to the type of sensory/perceptual requirement. Figure 5 exhibits the difference in these probabilities by type of activity (work vs. personal) and by type of requirement. The results indicate that activities that require manual and visual resources are expected to increase quite substantially: +23.2 percentage points for personal activities and +10.9 percentage points for work-related activities that require visual resources, and +13.8 percentage points for personal activities and +10 percentage points for work activities that require manual resources.

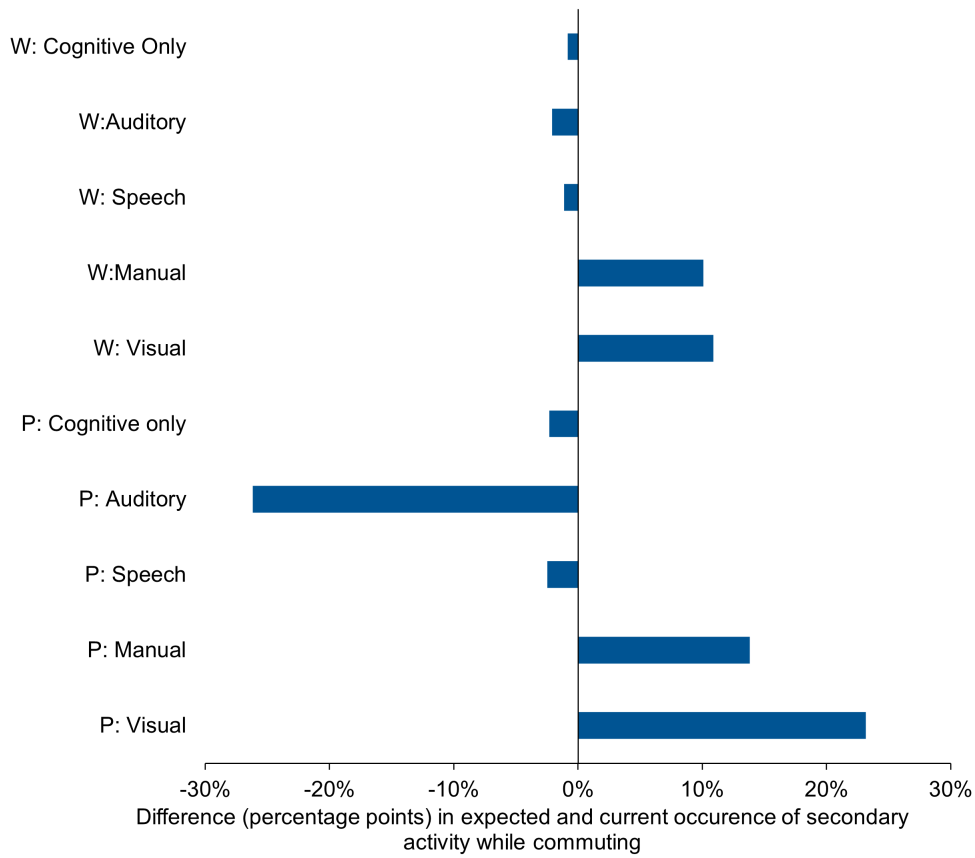

Figure 5: Difference in expected versus current secondary activities while commuting, by sensory/perceptual demand. This figure only considers morning and evening current commuting events, and their respective expected counterparts, for activities associated with some secondary activity. Current activities within a commuting event are re-weighted by a 1/N weight, where N is the number of total secondary activities in that same commuting event.

5. Discussion

The goal of this study is to understand how future automated vehicles can support the work and wellbeing of knowledge workers during their commutes. In particular, we seek to assess what tasks knowledge workers might want to do in future automated vehicles while commuting. Our findings shed light on how commuting fits into the work-day of knowledge workers, the extent to which knowledge workers engage in multitasking-while-driving behavior when commuting to / from work in current vehicles, as well as the work and personal-related non-driving tasks that knowledge workers currently engage in while commuting-by-driving. We also provide insight into what work-related and personal tasks knowledge-workers expect to engage in when driving in future safe highly-automated vehicles.

First, our results indicate that commuting time mainly substitutes personal time. This crowding out effect of commuting on personal time is consistent with the ATUS data (United States Bureau of Labor Statistics, 2018). Our findings also show that drivers use their commute time to compensate for some of the lost personal time by engaging in secondary activities such as listening to music, thinking and reflecting, calling friends and family, and listening to podcasts and audiobooks. Given that commuting time crowds out personal time it is perhaps unsurprising that commuting-by-driving time seems to negatively correlate with overall life-satisfaction across otherwise similar participants. This result, while only suggestive, is consistent with the ATUS data (United States Bureau of Labor Statistics, 2018) and other research on the relationship between commuting and wellbeing (Hilbrecht et al., 2014, Stutzer and Frey, 2008, Kahneman et al., 2004). (Q1)

Second, knowledge workers, *currently* engage in both personal and work-related activities while driving (see Figure 3). More than 80% of commuting events involve multitasking - drivers operate their vehicles and are engaged in at least one secondary (non-driving related) task, while in 35.5% of commutes participants reported engaging in 2 or more tasks while driving. In both morning and evening commutes, participants are more likely to engage in *personal* activities. However, secondary work related activities are more likely to occur in morning rather than in evening commutes (results in section 4.3). Work related activity also tends to be more intense in the morning, with about quarter of the commutes involving two or more secondary work activities (see Figure 4). (Q2)

Third, while driving, knowledge workers engage in various personal and work related activities that require the use of visual, cognitive and manual resources.

This includes reading and writing emails, browsing social media, analyzing and programming, all of which are tasks that are *not* compatible with safe driving (see Table 2). In particular, about a third of *work* related activities in morning commutes have visual and manual requirements (22.8% in evening commutes), while about 30% of morning work-related activities have manual requirements (20%). Personal activities to a larger extent, rely on auditory modality (see Figure 4). (Q3)

Fourth, results indicate that commuting currently serves as a transition - rather than a continuation - period. Commuting separates personal and work activities, and exact continuation of activities between commuting and work activities is relatively rare. However, multitasking while commuting is connected to other activities that individuals perform outside the commute, with few activities exclusive to the car environment (e.g. listening to music/radio). The lack of continuation could be attributed to the fact that the car is still a limiting environment to engage in many of the core activities knowledge workers engage in during their day, and in particular immediately after or before their commute (see Table 3). (Q4)

Finally, findings from this study allow us to evaluate which activities knowledge workers expect to engage in while driving a future safe highly automated vehicle. Overall, we see persistent preferences: most of the individuals who reported that they currently work during their car commute would continue working in an AV, and about 70% of individuals who currently perform personal activities would continue performing personal activities in a highly-automated vehicle. In terms of specific secondary-activities, knowledge workers are expecting to engage in more activities with visual and manual resource demands such as writing emails, browsing social media, programming, and watching videos, and less in activities that rely on auditory and mental only demands (see Table 4 and Figure 5). (Q5)

Taken together these findings have implications for the design of technology for supporting work and wellbeing activities in AVs.

5.1. Implications for Design

Here we discuss design implications for technology supporting work and wellbeing activities while *commuting by driving* using an AV. It is important to note that engaging in secondary tasks while driving can reduce attention to the road, as well as the driver's ability to physically control the vehicle, and hence can reduce driving safety (Medenica and Kun, 2007). Thus any technology for supporting secondary tasks while the driver is responsible for driving for the entire or parts of the commute, must be designed and evaluated for safe driving.

5.1.1. Supporting secondary tasks across automation levels

As evidenced by our findings, drivers are *currently* engaging in various work and personal secondary tasks that are not compatible with safe driving. This indicates a crucial need to support such activities, while prioritizing safety, across different levels of vehicle automation (SAE J3016, 2016), starting with vehicles that have adaptive cruise control and steering assistance (automation level 2). These vehicles are already available, and can make driving less taxing as well as support driving safety. However, the systems in these vehicles are designed as assistance systems for a driver who is continuously in control of the vehicle. This means that drivers need to use their manual and visual resources primarily for the driving task. Unfortunately, some drivers might put too much trust into the capabilities of the level-2 automation and assume that the automation is able to safely drive without human supervision. In such a case of overtrust (see (Lee and See, 2004)) the driver might not be prepared to take action if the automation fails. Any technological tools for supporting in-vehicle secondary (non-driving) tasks in level-2 automated vehicles must help drivers avoid overtrusting automation - these tools must first and foremost focus on supporting the driving task and only then the non-driving task.

We expect that vehicles with level-3 automation will become increasingly available in the near future. These vehicles will in fact take full control of the vehicle, but only under some circumstances (e.g. slow, bumper-to-bumper traffic on a multi-lane highway), and only for a limited time. Drivers will be able to engage in non-driving tasks safely, but will need to return to driving quickly when so instructed by the automation. Our findings indicate that workers are likely to engage in more cognitively and visually demanding activities such as writing and editing emails and documents, programming and analyzing data, as well as watching video. In this case our technological tools for supporting non-driving tasks will again have to be carefully designed to avoid overtrust - drivers must realize that it is critical for them to return to driving when so instructed. To do so effectively, it will be necessary to support drivers in maintaining an awareness of the road and the vehicles that surround them. One way to do this is to help drivers look at the road ahead even if they are engaged in non-driving tasks, and speech based interfaces might be helpful to do this. Speech interfaces are already common in cars (Lo and Green, 2013, Tashev et al., 2009, Miller and Kun, 2013), however, technologies such as in-car intelligent speech-based assistance (e.g. Microsoft's Cortana Cortana, Amazon's Alexa (Gartenberg, 2018), or Intuition Robotics' AutoQ (Intuition Robotics, 2019)) could provide additional cognitive support for more complex tasks involving both reading and writing in lower automation levels, which require the driver to focus on the road continuously. Martelaro et al. (2019) demonstrated the feasibility of this approach.

Note that one possible consequence of being able to work and relax in an automated vehicle is that people might spend more time in these vehicles than they do now. This is especially true for vehicles with automation level 4 and 5 (see e.g. Stevens et al. (2019)), but could also be the case for vehicles with level-3 automation. However, sitting for long periods of time in a vehicle can lead to pain in the lower back, neck, shoulders, and arms (Magnusson and Pope, 1998). And of course, if people look away from the road in order to interact with user interfaces, many will suffer from motion sickness (Diels and Bos, 2016, Sivak and Schoettle, 2015). The in-vehicle user interfaces that we design for automated vehicles must address these issues.

5.1.2. Supporting transitions between secondary tasks and driving

When using an AV, workers would use new interfaces, similar to the ones described above, to engage with work and personal related secondary activities while automation takes over the driving task. When the AV requests that the driver take over the driving tasks, they will have to return to the driving task, thus the interface will need to hide secondary task functionality. But removing the secondary task functionality too quickly might leave the user confused and resentful when work is lost. It might also change how they behave when the functionality is available, for example trying to rush through tasks (c.f. (Brumby et al., 2011)). All of this could ultimately lead to unsafe driving. For this reason it is important to carefully design not only the transition from the non-driving task to driving, but also the support when drivers transition back to their secondary task from driving. We expect that, if drivers know that this support is available, they will transition from the secondary task to the driving task more readily, because they will not fear that interrupting their secondary task will incur a high performance cost on that task. Recent work proposes to handle such transitions as multi-stage interruptions (Janssen et al., 2019). More research is needed in order to assess the appropriate amount of time that users need to complete various work or personal tasks and transition back to driving. Our findings highlight which tasks (see Table 4) to prioritize in the investigation and design of such transitions.

5.1.3. Supporting transitions to and from personal time

Our findings show that commuting serves as a transitional period, separating work and personal time. We also show that commuting time mainly substitutes personal time and that commuters currently use their commute time to compensate for some of the lost personal time. However, our results show that when using AV, knowledge workers are more likely to switch from personal to work-related activities in the morning rather than in the evening commute. In-vehicle technology can play an important role in helping workers to transition to and from personal time. For example in the morning commute in-vehicle technology could provide support for planning, preparation, and meetings. Similarly, during the evening commute, in-vehicle technology could help workers to transition back to personal time through support for reflection, social connection, and post-work recovery. Recent works explore the feasibility of using digital games (Collins et al., 2019) and intelligent agents (Williams et al., 2018) for promoting post-work recovery and workplace detachment - similar applications could be designed for in-vehicle use. Microsoft demonstrated the feasibility of this approach by integrating a 'virtual commute' feature into their Teams product, intended to reestablish boundaries between work and personal time, when working from home (Deighton, 2020). Other ways to help workers reclaim personal time would be to provide in-vehicle support for completing personal tasks and for promoting social connectedness.

5.1.4. Support for different contexts

Finally, the study results suggest that the use of AVs will affect the commuting experience of workers in heterogeneous ways. Our findings indicate that the *timing of commute* (morning or evening) impacts the secondary tasks workers choose to engage in while driving. Other variables, might also impact the commuting experience of workers and their preference between work and personal activities. Berliner et al. (2015) studied how individual-specific traits affect commuters' propensities to engage in activities while traveling, and found that a wide range of variables including age, gender, income, trip distance, education level, attitudes and preferences towards the adoption of technology, familial obligations, etc. affect the propensity to engage in activities while commuting.

These variables should be considered in the design process of AV technology for supporting work and wellbeing activities, as well as in tailoring such technology for workers' specific needs. For example, expert systems could help workers by proposing micro tasks or scheduling meeting based on the timing or duration of the commute, or within the time frame in which the automation is driving.

5.2. Limitations and Future Work

This study has several limitations that we intend to address in future work. First, this study utilizes an adapted version of the Daily Reconstruction Method

(DRM) survey, which ask participants to report on activities they conducted in a representative work day from the previous week. The DRM method is widely used and is considered less burdensome than diary studies, but it is important to note that people might have an inaccurate memory and their responses might be less accurate when compared to data collected during the day in a diary study (Diener and Tay, 2014). Related limitations associated to the survey design are: (1) participants were only asked about their expected preferences for multitasking in a highly automated vehicle after having filled their time-use diary, which could introduce some order bias if such ordering heightened preferences for engaging in secondary tasks in a highly automated vehicle; (2) our method does not capture details of the conditions in the commuting event that may have enabled multitasking (e.g. whether participants engaged in multitasking only when stopping in traffic lights); and (3) the survey does not capture time use associated to the duration of the secondary activities, rather focusing on time use of the primary activity (commuting). To cope with some of these limitations, we plan to follow up on this study with a longitudinal diary study. In addition, future research could investigate the conditions and timing within commuting events that facilitate multitasking while driving.

Second, we conducted the study with a population of knowledge workers from the United States, where in many areas access to public transportation is limited. It is important to deploy this study in other countries where cultural and structural factors might result in differences in knowledge workers' experiences, preferences, and expectations.

Third, in this study we focused on knowledge workers who are likely to be early adopters of AVs. However in order to ensure that the design of technology for supporting work and wellbeing in highly automated cars is inclusive and benefits everyone, there is a need to study different populations of workers and commuters. Effectively, this study focused on knowledge workers who commute by driving themselves to and from work, which limits extrapolations of our findings to knowledge workers who commute using other means of transportation (e.g. passenger in ride-sharing or the use of public transportation). Future work could replicate our study to encompass a larger sample of workers, such as workers who commute using public transportation or even non-knowledge workers who may also leverage an autonomous vehicle experience to support their daily routines in ways that are different than directly conducting work tasks while commuting.

Fourth, we asked commuters about their expected activities when commuting in a future (hypothetical) safe self driving car. However, there might be a gap between participants' responses and their actual behavior when using a self driving car. We plan to follow up on this study by examining participant behavior in experiments where we simulate AVs, either using a driving simulator, or by driving participants (c.f. (Wang et al., 2017, Krome et al., 2016)). A related limitation is that our study did not account for whether participants had familiarity with human-computer interaction technologies or their potential to support multitasking while driving. As a result, their responses about expected behavior when commuting in an autonomous vehicle may be driven by misinformation about the potential functionalities of autonomous vehicles rather than effective preferences.

Fifth, the study collected quantitative information about the experiences, preferences, and expectations of knowledge worker commuters. However, our comparison of expected and current engagement in multitasking while driving is limited by our survey design that enables participants to select multiple secondary activities in the time-use diary, but only a single expected secondary activity for the morning and a single expected secondary activity for the evening commute in case the participants had access to an autonomous vehicle. Although we selected this approach to highlight the main secondary task that individuals expect to conduct in a highly automated vehicle, this choice limits the comparability of expected and current multitasking while driving. Furthermore, our study does not explore the nature of "multi-multitasking" while driving, that is, when workers engage in multiple activities simultaneously while driving. One potential alternative to this approach is to engage in qualitative investigations that provide nuanced understanding of workers' motivations, challenges and desires. Future work will include a series of in-depth ethnographic studies of commuting managers and workers.

Finally, our results indicate that, given a self-driving car, knowledge workers would engage in the same tasks they already engage in, with some shifts in time allocation. Would this result hold if we informed participants of some of the HCI technologies that could improve their work and wellbeing activities in cars? Furthermore, how would users' level of acceptance of automated vehicles (Nordhoff et al., 2019) influence their expectations of what they can do in future automated vehicles? To explore these questions we plan to organize workshops in which participants with different backgrounds will design in-vehicle interactions using speech interaction, augmented reality, and tangible interfaces.

6. Conclusion

Automated vehicles are likely to be on our roads soon. These vehicles will present enormous opportunities and challenges in many aspects of our lives. In this paper, we explore how AVs will affect the work and wellbeing activities of knowledge workers during their morning and evening commutes. As a baseline, our results clearly indicate that knowledge workers already engage in a wide variety of work and wellbeing activities. Some of these activities are not safe to perform while driving. For this reason alone AVs can be a benefit: if we design the user interfaces well, they will support workers in non-driving activities when automation is in charge, and then help them stay focused on the driving task when it is their turn to drive.

Our results also indicate that in AVs knowledge workers will take advantage of their newfound freedom from driving and will expand engagement in both work and personal activities. We should build on this result and design systems that help workers strike a balance between work productivity and personal wellbeing as they engage in secondary activities during their commutes in AVs. Upcoming work, including experiments, interviews, workshops, driving simulator and on-road studies, will further explore various aspects of this complex issue.

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Appendix

	[1]	[2]	[3]	[4]	[5]	[6]
Dependent variable	Ln(Time reported in work-related activities)		Ln(Time reported in personal activities aside from sleeping)		0-10 cantril ladder score (life satisfaction)	
Ln(Time reported in commuting activities)	-0.0964*	-0.1000*	-0.3673***	-0.3572***	-0.4008***	-0.3058**
	[0.0787]	[0.0990]	[0.0007]	[0.0010]	[0.0055]	[0.0365]
Observations	400	400	400	400	399	399
Adjusted R-squared	0.4732	0.4665	0.3487	0.355	0.0634	0.1682
Socioeconomic control variables	No	Yes	No	Yes	No	Yes
Work-related control variables	No	Yes	No	Yes	No	Yes
Noise control variables	Yes	Yes	Yes	Yes	Yes	Yes

Table A1: Regression results: substitution of commuting time per spent work-related time, substitution of commuting time per personal time, and conditional correlation between commuting time and well-being score. Significance levels: *** p-value < 0.01, ** p-value < 0.05, * p-value < 0.1. All standard errors are White-Huber standard errors robust to heterokedasticity. A list of the the socioeconomic, work-related, and noise control variables are in the main text.

Begin of Table A2

	[1]	[2]	[3]
Dependent variable	Ln(Total time in work-related activities)	Ln(Total time in personal activities aside from sleeping)	0-10 cantril ladder score (life satisfaction)
Ln(Total time in commuting activities)	-0.1000*	-0.3572***	-0.3058**
	[0.0990]	[0.0010]	[0.0365]
Total time in the survey (in minutes)	0.0001	0.0001	0.0015
	[0.8012]	[0.7892]	[0.2179]
Day of week (baseline: Monday)			
Tuesday	-0.0329	0.0293	0.0783
	[0.6114]	[0.7814]	[0.7103]
Wednesday	0.0093	0.1141	0.0698
	[0.8358]	[0.2199]	[0.7683]
Thursday	0.1205*	-0.1	0.1761
	[0.0694]	[0.3485]	[0.5578]
Friday	0.1203	-0.5673	-0.4117
	[0.2668]	[0.2471]	[0.4470]
Ln(Total time reported in time diary)	1.1859***	1.9295***	-0.8493***
	[0.0000]	[0.0000]	[0.0056]
Dummy: female=1	0.0389	-0.0879	0.1704
	[0.3844]	[0.3700]	[0.3304]
Dummy: children living with respondent=1	-0.0314	0.2713**	0.107

Continuation of Table A2

Number of people living with respondent (including self)	0.005	-0.0860*	0.0987
	[0.8104]	[0.0830]	[0.2427]
Annual salary (baseline $40kto60$k)			
$60kto80$k	0.119	-0.0773	0.2415
	[0.1082]	[0.3926]	[0.3698]
$80kto100$k	0.1706**	-0.3865**	0.5877*
	[0.0347]	[0.0119]	[0.0511]
$100k or higher	0.1550*	-0.1353	0.8392***
	[0.0814]	[0.2821]	[0.0033]
Education (baseline: high school)			
College degree	-0.0164	0.0664	-0.0559
	[0.7839]	[0.6156]	[0.8112]
Graduate degree	-0.0662	-0.0601	0.2191
	[0.3401]	[0.6911]	[0.4021]
Dummy: older than 40 years old=1	0.0796*	0.0012	-0.1081
	[0.0519]	[0.9883]	[0.5802]
Dummy: manager=1	-0.0465	0.0268	0.1581
	[0.4067]	[0.7329]	[0.5792]
Ln(number of employees in firm)	-0.0046	0.0057	0.1273***
	[0.6228]	[0.8010]	[0.0028]

Continuation of Table A2

Industry (baseline: Agriculture, Forestry, and Fishing)			
Industry: Mining	-0.1487	0.1618	-0.3136
	[0.5177]	[0.6733]	[0.7160]
Industry: Construction	-0.0282	-0.4095	-0.3023
	[0.8907]	[0.1714]	[0.5891]
Industry: Manufacturing	-0.0567	-0.2562	-0.2909
	[0.7601]	[0.3135]	[0.6125]
Industry: Transportation, Communications, Electric, Gas, and Sanitary Services	-0.0421	-0.1733	-0.0579
	[0.8361]	[0.4764]	[0.9213]
Industry: Wholesale Trade	0.013	-0.1705	-0.3494
	[0.9504]	[0.5431]	[0.5968]
Industry: Retail Trade	-0.0533	-0.0722	-0.4223
	[0.7854]	[0.7681]	[0.4552]
Industry: Finance, Insurance, and Real Estate	0.0354	-0.3778	-0.3038
	[0.8497]	[0.1576]	[0.5934]
Industry: Services	-0.0339	-0.1045	-0.1942
	[0.8554]	[0.6355]	[0.7062]
Industry: Public Administration	-0.1106	0.0229	-0.8507
	[0.5698]	[0.9187]	[0.1463]
Industry: not reported	-0.1371	-0.2891	-0.5971

Continuation of Table A2

Size of city of work (baseline: Large Metropolitan Area - population>1.5M)			
Metropolitan Area *(population between 500k and 1.5M)*	-0.0326	0.125	-0.1371
	[0.7500]	[0.4911]	[0.6634]
Medium-sized Urban Area *(population between 200k and 500k)*	-0.1156	0.3269*	0.6007*
	[0.2835]	[0.0632]	[0.0626]
textit Small-sized Urban Area (population between 50k and 200k)	0.0008	0.1778	0.3345
	[0.9936]	[0.3228]	[0.4312]
Rural Area	0.0436	0.0708	0.2677
	[0.6360]	[0.6561]	[0.5319]
Dummy: work-home distance >6 miles=1	0.0181	0.0103	-0.3362*
	[0.7741]	[0.9072]	[0.0810]
Constant	-1.5697**	-5.3508***	12.4729***
	[0.0394]	[0.0016]	[0.0000]
Observations	400	400	399
Adjusted R-squared	0.4665	0.355	0.1682

Table A2: Regression results (all control variables): substitution of commuting time per spent work-related time, substitution of commuting time per personal time, and conditional correlation between commuting time and well-being score. Significance levels: *** p-value < 0.01, ** p-value < 0.05, * p-value < 0.1. All standard errors are White-Huber standard errors robust to heterokedasticity.

Primary Activity Titles (as entered in time-use diary)
Commuting: to/from work; for trips during work
Work: working alone - reading/replying emails
Work: working alone - browsing/checking social media/messaging
Work: working alone - planning/preparing/thinking (e.g. a presentation/document/program/product)
Work: working alone - writing/editing/programming (e.g. a presentation/document/program/product)
Work: working alone - reading/analyzing (e.g. presentation/document/program/product)
Work: phone call/conference call/video-conference
Work: in person meeting (e.g. one on one, with many)
Work: leisure with colleagues or clients
Work: other activity
Personal: sleeping
Personal: relaxing/resting
Personal: reading/browsing/social media/email/messaging
Personal: watching video/tv
Personal: praying/worshiping/meditating
Personal: exercising (e.g. jogging/competitive sport/yoga etc.)
Personal: charity, volunteering
Personal: preparing food/housework/taking care of children
Personal: eating/drinking
Personal: phone call
Personal: leisure with family/friends
Personal: other activity

Table A3: List of primary activities that participants could enter in the time-use diary.