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Replacement of distractions with other distractions: A propensity-based approach to estimating realistic crash odds ratios for driver engagement in secondary tasks

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ABSTRACT

As Automated Vehicles (AVs) enter the fleet at lower levels of automated (SAE, 2018), the need for human drivers to remain engaged in the driving task will continue. Thus, understanding driver distraction and estimating the reduction in risk associated with removing distractions is important as AV technology develops. While previous research (e.g., Dingus et al., 2016) has estimated large odds ratios (i.e., 3–4) for using cell-phones while driving, countermeasures directed at reducing cell-phone use have not realized large crash reductions. One reason may be that drivers may replace cell-phone use with other risky activities and that odds ratios (ORs) have often compared cell-phone use to ideal driving rather than a realistic reference. Using data from the second Strategic Highway Research Program (SHRP2), we developed two cell-phone propensity models, one with age and one without, to develop weights for events without cell phone use. Using these weights, we estimated the probability of engagement in a variety of tasks in place of cell-phone use. We also estimated weighted odds ratios for cell-phone use (all uses) and cell-phone talking only. Weighted ORs are lower than unweighted ORs and much lower than ORs compared to ideal driving. This is consistent with the idea that in practice, even if cell-phone bans are effective at reducing cell-phone use, they may not greatly reduce risk because drivers may replace cell-phone use with other distracting activities in the same situations in which they normally use cell phones while driving. We also discuss the influence of young drivers on our results. Younger drivers in the dataset are more likely to use cell phones and thus are influential in the propensity model results.

1. Introduction

The Society of Automotive Engineers (SAE) has developed a taxonomy describing six levels of vehicle automation (Society of Automotive Engineers (SAE) (SAE), 2018). Within this taxonomy, Levels 0 (no automation), 1, 2, and 3 all require driver action under some circumstances. As a result, the ability of the driver to respond to an imminent safety problem is of critical importance. In particular, driver distraction – drivers performing tasks other than driving or monitoring the automated vehicle (AV) driving – has been a key safety issue that has been studied for decades (e.g., Treat et al., 1977). Moreover, it is one

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that may be of greater concern as AVs absorb much of the driving task, yet rely on human drivers, who may be even more disengaged because of reduced workload, to take over on demand.

One of the ways that this is being addressed in partially automated vehicles is through the use of secondary-task countermeasures. These include technological countermeasures such as cell-phone blockers, driver monitoring systems, and vehicle or smartphone settings that prevent cell-phone use during driving. On a larger scale, legislative countermeasures target specific secondary tasks (generally texting or any cell-phone use).

To understand how these technologies may improve safety, we need good estimates of relative crash risk associated with involvement in specific secondary tasks. For countermeasures associated with cell-phone use (including texting), we turn to naturalistic driving studies (NDS) to provide estimates of the associated change in risk (when the driver is engaged in cell-phone-related tasks). For practical use, this risk ratio estimate is interpreted as the increase in risk if drivers are engaging in cell-phone use.

Previous research using data from the second Strategic Highway Research Program (SHRP2) NDS reported that the estimated odds ratio (OR) of crashing associated with cell-phone use while driving was 3.6 (CI: 2.9–4.5), when compared to ideal driving (also called "model driving"), in which drivers were not fatigued, impaired or engaging in any secondary tasks (Dingus et al., 2016). Related work using crash data (e.g., McEvoy et al., 2005) has led to cell-phone bans being passed in various states and countries.

In spite of the evidence for risks associated with cell-phone use, the expected benefit of bans on crashes has not been realized. In the U.S. an analysis of states that banned cell-phone use when driving showed that the bans reduced cell-phone use but not insurance claims (Insurance Institute for Highway Safety, 2014). In Europe, the UDrive study found large differences in mobile-phone use in driving by country (Carsten et al., 2017). German drivers used mobile phones 0.06% of the time as compared to UK (2.87%), French (3.48%), and Polish (9.49%) drivers. All of these countries have mobile-phone bans while driving though very different rates were observed in the data.

One hypothesis for the failure to realize large reductions in crash counts where mobile-phone bans are in place is that drivers who are not using their cell phones may engage in different secondary tasks and be distracted by other means. Since NDS-based OR estimates for cell-phone use are often calculated using ideal driving as a reference activity, it may be that these ORs overestimate the potential benefits that can be realized in actual driving when cell-phone use is reduced. That is, drivers are unlikely to replace cell-phone use with ideal driving, since they are engaged in secondary tasks frequently (more than half the time in SHRP2; Dingus et al., 2016). However, evidence for self-limiting (e.g., Flannagan, Bao, & Klinich, 2012) also suggests that because cell-phone use is not random with respect to driving conditions, drivers may not replace cell-phone use with other activities completely at random either. Thus, the question is: What is an appropriate reference activity that better reflects the likely activities with which drivers will replace cell-phone use? In addition, what is the OR for cell-phone use when compared to the likely replacement activity?

In this paper, we approach this problem by developing a new reference in which non-cell-phone events are weighted by the probability that the driver would have used a cell phone in that event, given the context present. Here, context is defined as environmental characteristics (e.g., traffic density, time of day) and driver characteristics (age, gender). This approach is similar to propensity weighting (Freedman & Berk, 2008; Månsson, Joffe, Sun, & Hennessy, 2007) in that we create a cell-phone-use propensity model that is applied to each event. However, propensity weighting is typically used to correct for overrepresentation of certain cases (based on their covariates) in the treatment group relative to random assignment. Here, we have a random sample of all driving but want it to be a random sample of the driving conditions that are present when drivers are on the cell phone. Thus, we weight events by their cell-phone-use propensity. In this way, cell-phone crash odds are compared to reference driver behaviour and crash risk should better reflect the expected behaviour and crash risk when cell-phone use is discouraged (e.g., by legislative or technological means).

Although we apply the method to cell-phone use as a secondary task, our objective is to demonstrate how the method can change estimates in a way that should be more realistic in practical terms. The objectives of this study are: (1) Introduce the use of propensity weighting to estimate what drivers are doing when not engaged in a given task or tasks; (2) Demonstrate the use of the method to identify what drivers are doing when they are not on the cell phone; and (3) Estimate the OR for cell-phone use when compared to the set of activities that would be expected to replace cell-phone use in the case of a ban. As automation changes drivers' incentives to engage in different tasks, both by removing some of the driving task requirements and by monitoring and alerting drivers when they are engaged in various secondary tasks, it will become increasingly important to understand what alternatives they are choosing and how those alternatives might affect their readiness to take action in critical situations.

2. Method

For this analysis, we used data from the SHRP2 study. SHRP2 is a naturalistic driving study that was conducted in six locations in the U.S. from 2012 to 2013. Approximately 3,400 vehicles were monitored with Data Acquisition Systems (DASs), which collected video and kinematic data continuously while the vehicles were driven. This resulted in a total of approximately 5.5 million trips with consented drivers (i.e., study participants, whose data are available for analysis) and approximately 56 million kilometres of driving (Hankey, Perez, & McClafferty, 2016).

As part of the original study, a set of safety-critical and non-safety-critical (baseline) events were extracted from the larger dataset. Safety critical events (SCEs) in the dataset include crashes (as well as near-crashes, which we did not use). In addition, a set of clips, known as "balanced baselines," were selected at random from all driving over 5 mph. The number of clips selected per driver was proportional to his/her total driving time in the study.

Crashes were defined as:

> "Any contact that the subject vehicle has with an object, either moving or fixed, at any speed in which kinetic energy is measurably transferred or dissipated is considered a crash." (Hankey et al., 2016)

In addition, crashes were further categorized into Level I, II, III, and IV, in order of decreasing severity, based on video review. Level I is a severe crash, Level II is a moderate crash, Level III is a minor crash, and Level IV is defined as a low-risk tire strike. Detailed definitions and extraction methods can be found in Hankey et al. (2016).

For this analysis, we only used those crashes where the first event was coded as a Level I, II or III crash. Each baseline or crash clip was 20–30 s long but was only video-coded for 6 s. Video coding was done for the 5 s prior and 1 s after the identified precipitating event for crashes and for a random 6 s for baselines. This resulted in a dataset with 19,991 balanced-baseline cases and 830 crashes.

We developed our cell-phone propensity model using logistic regression to predict the probability of using the cell phone as a function of available covariates, which included:

- Relation to junction—spatial relationship of vehicle to a junction, if any
- Intersection influence—judgment of whether an intersection influenced driving behaviour such as braking
- Traffic flow[1]—roadway design, including number of lanes and presence of dividers
- Traffic density (Footnote 1)—traffic density for the specific event, coded from free-flow to flow restrictions (stop-and-go)
- Front seat passengers—codes presence or absence of a front seat passenger
- Lighting—light level coded from forward video (e.g., daylight, dusk/dawn, dark but lighted, dark)
- Weather—weather conditions coded from forward video
- Surface condition—road surface condition coded from forward video (e.g., wet, dry, icy)
- Through travel lanes—number of lanes in driver's direction of travel (does not include turn lanes)
- Day of week
- Locality—Coded surroundings e.g., residential, business, rural, etc.
- Mean travel speed during full event
- Driver age group—first group includes ages 16–19 (4 years) with 5-year groupings thereafter

All cell-phone interaction types, both with hands-free and hand-held phones, were included in the propensity modeling as "cell-phone positive", though talking on a hand-held phone makes up the majority of cases (1656, or 92%). All remaining tasks, including no secondary tasks, were treated as "cell-phone negative" in the logistic regression.

Using the regression approach described above, we estimated two propensity models, one excluding driver age and the other including driver age. The first model was intended to capture the effect of environmental variables that might influence drivers to either use or not use the cell-phone while driving. The second model included the effect of driver age since young drivers are known to use cell-phones more often than older drivers (Guo et al., 2016.

Only baseline cases were used for the propensity model since if cell-phone use itself increases risk, we would expect crash cases to include cell-phone use with higher probability across all conditions. The model was then used to compute the predicted probability of being on the cell phone for all events (both crashes and baselines) in which the driver was *not* engaged in a cell-phone task. The 19,018 non-cell-phone events were weighted according to the predicted propensity of using the cell phone in that event. The weights for non-cell-phone events were computed by taking the values of each of the covariates for that event (e.g., driver age, relation to junction, etc.), and entering them into the propensity model equation. The output of the model is then the predicted probability of the driver using a cell-phone in that event, based on the event's covariate characteristics. Additionally, to extend weighting to all events, the 1803 crash and baseline events where cell phones were in use were given a weight of 1, which can be convenient in the implementation of the method in statistical software. Note that any non-zero weight value assigned equally to all cell-phone-used events would yield the same OR estimates.

To estimate the prevalence of other tasks in lieu of cell-phone-use, we used balanced baseline events where cell-phone use was absent, weighted by propensity. The weighted proportion of each alternative task (as well as no secondary tasks) occurring in that sample was used to estimate the probability of that task replacing cell-phone use if cell-phone use were eliminated from driving. The full list of secondary tasks coded is available on the InSight[2] website; the most common tasks include talking to passengers, external distractions, talking/singing, etc.

We also computed the cell-phone OR compared to the likely set of baseline activities using the propensity-score weights for the reference group. The ORs were estimated using logistic regression with no covariates in the model. This is equivalent to the 2X2 table in Fig. 1 below.

[1] Note that the terms "traffic flow" and "traffic density" are as used in the SHRP2 codebook (Hankey et al., 2016); these uses can conflict with other uses of these terms (e.g.., "traffic flow" is often defined as the movement of traffic at a particular location and point in time).

[2] https://insight.shrp2nds.us/login/auth#/builder.

	Cell Phone Used	
	Yes	No
Crash	a	b
Baseline	c	d

*Shaded cells are weighted in analysis

Fig. 1. Illustration of weighted odds ratio calculation.

The standard OR equation based on the cells in Fig. 1 is given in Eq. (1). The values *a, b, c* and *d* are cell counts. This is the calculation used in Dingus et al., 2016 where "no cell phone" (i.e., cells b and d) included only cases of ideal driving with no secondary tasks, fatigue or impairment.

$$OR = \frac{a/c}{b/d} \tag{1}$$

Eq. (2) shows how propensity weights are used in the same calculation. Here, we count all events where cell-phone use is absent (but there may be other secondary tasks) in cells b and d, and then we weight them as described in Eq. (2).

$$OR = \frac{\sum w_a / \sum w_c}{\sum w_b / \sum w_d} = \frac{a/c}{\sum w_b / \sum w_d} \tag{2}$$

where w_i is the sum of weights for events counted in cell *i*. (Recall that weights for cell-phone-used events are all equal, so the numerator will always be equivalent to a/c regardless of the specific value used.

3. Results

The dataset contained 3539 unique drivers. The age distribution is shown in Fig. 2 compared to the age distribution for licensed drivers in the U.S. Young drivers are substantially overrepresented and older drivers are also overrepresented but not to the same degree. Of the 19,991 baseline events, 1656 (8%) included some type of cell-phone interaction by the driver. Of the 830 crashes, 147 (18%) included cell-phone interaction.

We developed two cell-phone propensity models, one with and one without driver age group. Fig. 3 shows the distributions of predicted probability of cell-phone use for baseline events in which the cell-phone was (1) and was not (0) used for the two models. If drivers' cell-phone use is sensitive to the environmental and demographic conditions described by the covariates, we would expect that the distribution of propensities would be generally higher for those cases in which the cell phone was actually being used compared to those when it was not. This pattern was found for the model including driver age (right) but not when driver age was excluded (left). For the model without age, the mean predicted probability of cell-phone use was 0.0826 for events where the cell phone was not used and 0.0849 for events where the cell phone was used. The corresponding values for the model with age were 0.0796 (no cell) and 0.126 (cell used).

Using the two propensity weights resulting from the models without and with age defined for non-cell-phone events as described in the previous section, we first looked at the set of activities that drivers were engaged in when they were not on the cell phone, weighted by propensity. Using the unweighted baseline data, drivers were not engaged in any secondary task 46.7% of the time. The corresponding propensity-weighted estimates are 47% (no age) and 43.2% (with age). Of the remaining events, Fig. 4 shows the unweighted (stripes) and propensity-weighted distributions of task involvement for the model without age (gray) and with age (white).

Odds ratios and confidence intervals were computed using logistic regression with no covariates. Table 1 shows unweighted ORs relative to two different reference groups, as well as propensity-weighted estimates using each of the two propensity models. Following Dingus et al. (2016), the "ideal driving" reference group includes only those events where the driver was not engaged in any secondary task and was not impaired or fatigued (i.e., Driver Impairment variable="None"). All events that did not include cell-phone use or ideal driving were excluded from analysis. The "task absent" reference includes all events that do not include cell-phone use. Since all events are either in the numerator (cell-phone used) or denominator (no cell phone used), all events are included in analysis. Unweighted and weighted (with age) odds ratio estimates are also shown in Table 1 for the cell-phone hand-held talking only task, for comparison.

4. Discussion

A great deal of research has looked at the increase in crash risk associated with cell phone use while driving. This has led to legislation in many states and countries, but large hoped-for reductions in crashes (especially fatal crashes) have not been realized so far. One possible reason for this is that the estimates of crash odds ratios for cell-phone use are based on comparisons to idealized driving that is not achieved even when drivers are motivated not to use a cell phone while driving. In other words, drivers may replace cell-phone use with other secondary tasks that have similar risk profiles and thus not achieve the expected safety gains.

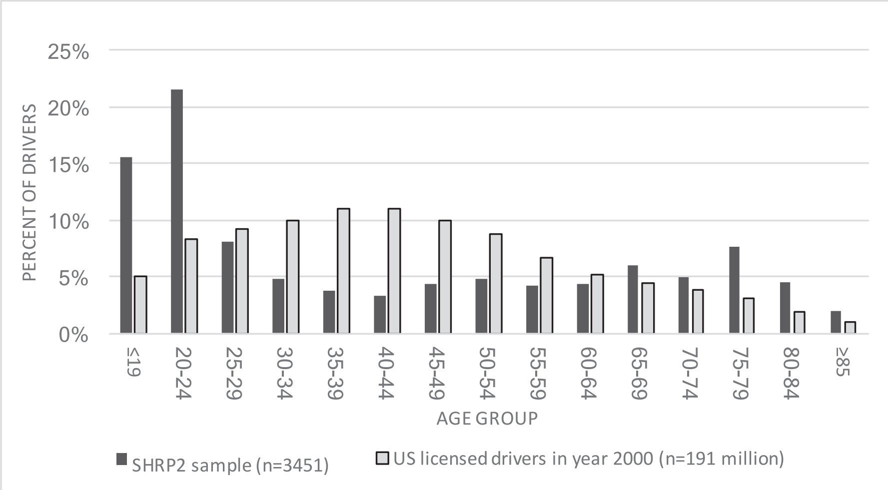

Fig. 2. Age distribution of drivers in SHRP2 and U.S. licensed drivers.

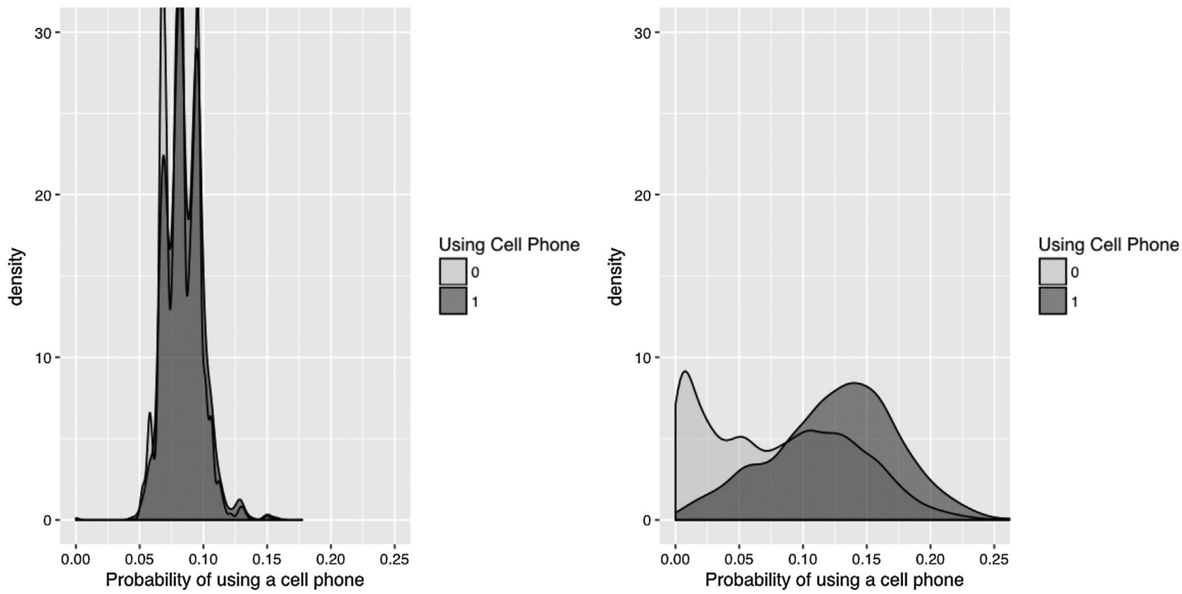

Fig. 3. Propensity distributions by cell-phone use for models without age (left) and with age (right).

In this and previous work (e.g., Klauer, Guo, Sudweeks, & Dingus, 2010), ORs using no secondary tasks or other forms of ideal driving are generally higher than those using "task absent" reference groups. We found that in the unweighted analysis, the confidence intervals of the two reference comparisons did not overlap. This is not surprising given that ideal driving is generally "safe" driving (i.e., attentive, sober).

The propensity-weighted models produced some interesting patterns. In particular, without age, we could not predict the situations under which drivers choose to use the cell phone. This conflicts with other published results, including one by the first author (e.g., Flannagan et al., 2012), that showed evidence of self-limiting of cell-phone use based on context. If drivers were strongly context-sensitive in their cell-phone use, the no-age propensity model should have done a better job of differentiating events with and without cell-phone use. Instead, the best predictor of cell-phone use was age, suggesting that the biggest contributor is the driver, not the situation.

In keeping with the poor differentiation performance of the no-age propensity model, the results of task involvement and ORs using weights from that model look very similar to unweighted results. However, when age is included, some tasks become more likely to occur (in cell-phone-likely situations) including talking/singing, dancing, and adjusting the radio. In addition, the point estimate of crash OR for cell-phone use is lowest using this model. Also, the estimated OR associated with hand-held cell-phone talking only, went down from 1.29 to 1.04 (both not significantly different from 1).

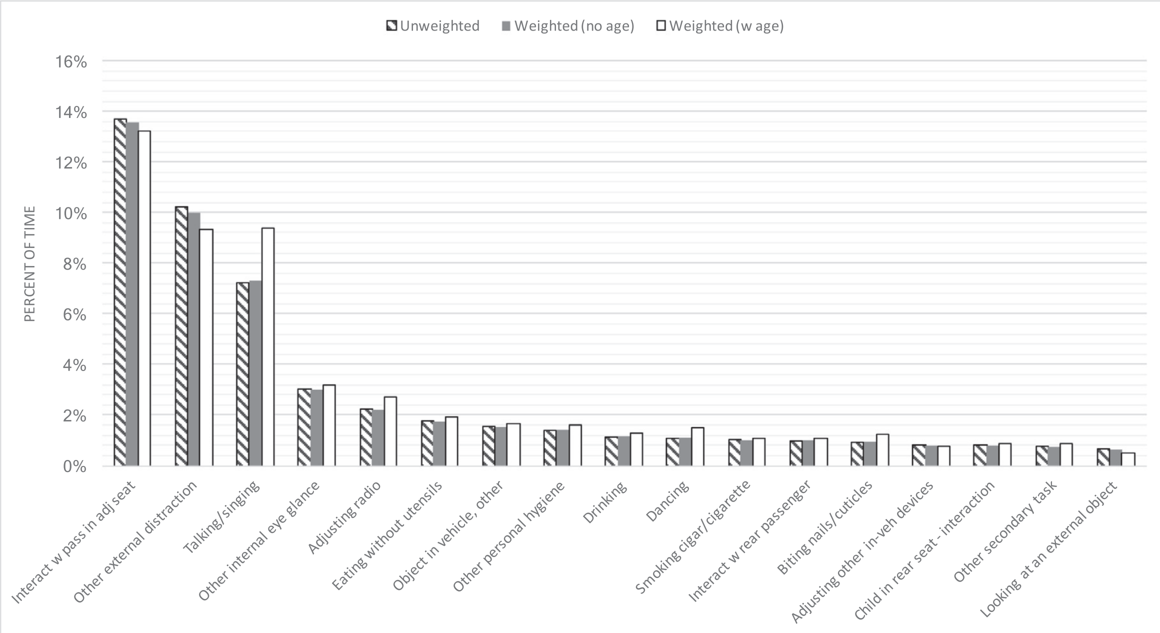

Fig. 4. Task involvement proportions using unweighted and two propensity-weighted models.

Table 1
Simple odds ratio (OR) estimates for crash risk associated with all cell-phone use using different reference groups and cell-phone talk only using unweighted and weighted (with age); HH = handheld.

Reference group	OR estimate	95% Confidence interval
All cell; Unweighted ideal driving	3.56	2.87–4.40
All cell; Unweighted task absent	2.38	1.97–2.86
All cell; Propensity weighted (no age)	2.45	1.80–3.39
All cell; Propensity weighted (with age)	1.98	1.48–2.70
Cell-phone HH talking only (unweighted task absent)	1.29	0.89–1.81
Cell-phone HH talking only (propensity weighted with age)	1.04	0.68–1.56

If age is the best predictor of cell-phone use and the largest contributor to cell-phone related risk, it may be necessary to think about the problem differently. Young drivers have long been shown to be riskier than other drivers (Massie, Campbell, & Williams, 1995), but cell phones have only been ubiquitous in driving for a decade. Moreover, using SHRP2 data, Guo et al. (2016) show that cell-phone associated crash risk was different for different age groups. Older drivers exhibited the most elevated crash OR for cell-phone use but rarely use the cell phone. Drivers from 16 to 29 also had higher ORs than middle-aged drivers but use the phone at higher rates. In the SHRP2 study, young drivers are overrepresented in the sample (relative to the population), are overrepresented in crashes (relative to other age groups), and are overrepresented in cell-phone use (relative to other age groups). Even in other studies, such as those using case-crossover designs and crash data, drivers under 29 make up a large portion of the sample (e.g., 48% in McEvoy et al., 2005). Thus, some portion of the estimated crash risk may be "borrowed" from risk specific to younger drivers.

It is important to note that although the risks associated with cell-phone use may have been overestimated in many studies (and in the popular press), we do observe a significant estimated crash OR of 1.98 for all cell-phone use in the age-included propensity-weighted model. Given the handheld cell-phone talking-only estimate of 1.04, the all-cell-phone-use risk must be associated with non-talking (and/or hands-free-talking) cell-phone uses.

In particular, texting is of special concern, having been demonstrated to be particularly risky in a number of studies (Caird, Johnston, Willness, Asbridge, & Steele, 2014; Dingus et al., 2016). In this dataset, which is now over five years old, texting was less common in the U.S. driver population than it is now. The annual driver behavior roadside study (Pickrell & Li, 2017) showed an increase in observed texting across all drivers from 1.5% to 2.1% (a 40% increase). Because of the low prevalence of texting in the dataset, we did not develop propensities or ORs specific to it. Based on the prevalence of texting among the young drivers in SHRP2 (3.32%; Guo et al., 2016 and our results, we expect that if we had sufficient data to build a propensity model for texting alone, age would play a key role, similar to the analysis done here. We would also expect the OR for texting to be lower than that reported by Dingus et al. (2016)–6.1 (CI: 4.5–8.2).

We should also note that although the overrepresentation of young people in SHRP2 may still inflate the OR somewhat, we do not claim that there is no risk or cause for concern. Instead, we have tried to develop a more appropriate estimate of the potential effect of removing cell-phones from the driving population by comparing their use to likely alternative behaviours.

This work could be extended in a number of ways. First, while we did not observe evidence of context-sensitive cell-phone use, it may be that young drivers have not developed this sensitivity while older drivers have. A follow-on study could develop age-group-specific propensity models, which we did not. Another improvement would be to reweight the drivers in SHRP2 to be better representative of the driving population. Finally, repeating this analysis on other NDS datasets such as UDrive would lend further insight into the factors that influence drivers' decision to use the cell phone when driving and improve estimates of crash ORs from cell phone use (and other distractions).

To extend to the vehicle automation context, the propensity approach can be used to evaluate a number of different technologies designed to maintain driver engagement. The key is to identify what behaviors are being targeted (this can even be "looking down for more than 2 s") and what drivers do otherwise under similar conditions. The age-specific, or even individual-specific propensity models may be particularly useful in this context so that such systems can become more sophisticated with respect to the ways drivers change their behavior that may not be the intent of the system.

Although the SHRP2 study is large, the number of crashes, especially relatively serious crashes, is still very small. In addition, the study population overrepresents younger and older drivers (relative to the U.S. driver population in general) and relied on self-motivated volunteers. Finally, mobile and in-vehicle technologies are changing rapidly, so even five-year-old data reflects a particular set of technologies and habits that have changed already. Thus, conclusions from SHRP2 may not fully generalize to the U.S. driver population. Moreover, since the study was conducted in the U.S., results may not fully generalize to the driver population in other countries. Finally, driver behavior may change as automation replaces drivers' need to engage more continuously in the driving task. Current studies are unlikely to capture these differences and thus we will need to keep updating studies as vehicles and drivers evolve.

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Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.trf.2019.04.013.

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