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Undercounting of cellphone use in police crash reports

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ABSTRACT

Introduction: There is widespread agreement that police-reported crash data undercount the number of crashes involving cellphones because cellphone use is difficult to identify as a crash contributor on-scene. This study investigated the extent of the underreporting by linking Cambridge Mobile Telematics crash data with data compiled from police crash reports to compare cellphone use as recorded by the responding officer with phone use as recorded by telematics.

Method: We linked nearly 17,000 crashes from police crash reports to crashes identified by telematics in four states between 2021 and 2024 by date, time, and location. Distraction as recorded by police was compared with phone use as recorded by telematics in the 30 seconds and 10 seconds prior to the moment that a crash was detected.

Results: Telematics data indicated that enrolled drivers had been using a cellphone within 10 seconds of 4% of single-vehicle crashes and 5% of two-vehicle crashes. Telematics data recorded phone use within 30 seconds of 7% of single-vehicle and 8% of two-vehicle crashes. Passive use of unlocked phones (such as navigation or watching a video) and manipulation (such as tapping or swiping) were the most detected, while handheld and hands-free calls were less common. Police crash reports reflected cellphone distraction in less than 1% of crashes. There were virtually no instances in which both datasets identified the same type of cellphone use as a crash factor.

Conclusion: This study suggests police crash reports may undercount cellphone use before a crash by a factor of at least 7. Practitioners should use caution when using crash data based on such reports to determine the extent that cellphone distractions contribute to motor vehicle crashes and injury.

1. INTRODUCTION

Regardless of the methodology used to estimate it, cellphone use while driving is alarmingly common (Cambridge Mobile Telematics [CMT], 2024; Cox et al., 2023; Dingus, 2014; Dingus et al., 2016; Hill et al., 2015). Over the last decade, drivers have also shifted how they use phones behind the wheel and are making fewer handheld calls and manipulating their phones more (CMT, 2024; Kidd & Chaudhary, 2019; National Center for Statistics and Analysis [NCSA], 2025). The most recent report from (CMT 2025b) showed that drivers are now spending over 2 minutes per hour manipulating their phone, about 4 times as long as they spend making handheld calls.

This change is worrisome because task complexity is directly related to crash risk (Klauer et al., 2006). Cellphone manipulation takes the driver's eyes away from the forward roadway and their hand(s) away from the steering wheel, so tasks like texting or interacting with apps or websites are associated with higher crash risk than less complex ones that allow the driver to keep their eyes on the roadway, such as talking on the phone (Choudhary et al., 2020; Dingus, 2014; Dingus et al., 2016; Klauer et al., 2006) or issuing voice commands with more modern technology. Looking away from the road for just 2 seconds doubles a driver's risk of being in a crash or near-crash event (Klauer et al., 2006).

Considering the high prevalence of cellphone use while driving, the increase in observed cellphone manipulation, and the high odds of crashing when engaging in complex tasks, we might expect the number of crashes where distraction and cellphone use are identified as contributing factors to be high. Yet, because distraction as a causal factor is difficult to prove (Blincoe et al., 2023; McCartt et al., 2006; NCSA, 2026; Ranney, 2008; Robertson et al., 2025; Trezise et al., 2006), the estimate that cellphone use was a factor in only 67,518 crashes (1% of all crashes) in 2024 (NCSA, 2026), is almost certainly low. Using the prevalence of cellphone use from naturalistic driving studies and its crash risk from the SHRP2 [1] Naturalistic Driving Study (Dingus et al., 2016), Blincoe et al. (2023) estimated

[1] SHRP2 = the second Strategic Highway Research Program.

cellphone distraction was a factor in closer to 6% of all crashes, or over 370,000 crashes, in 2024.

These estimates from Blincoe et al. (2023) offer a better picture of the impact of cellphones on crashes and injuries, but they may not be representative of the proportion of cellphone-affected crashes today. The 3-year naturalistic study that Blincoe et al. (2023) used to calculate estimates began in 2010 (Transportation Research Board, 2014) when 81%–89% of adults owned a cellphone, but smartphone ownership was only 35%–60% (Sidoti et al., 2025). The riskiest cellphone functions available to a large proportion of drivers were limited to dialing phone numbers to place a call and typing and reading text messages. As of June 2025, more capable smartphones accounted for 91% of cellphones owned. Drivers who participated in a recent nationally representative survey indicated they are still texting, but 20% self-reported doing other modern smartphone-enabled secondary tasks like playing a game or watching a video on at least most drives in the previous 30 days (Cox et al., 2023).

While the increased functionality of today's smartphones may come at the cost of traffic safety, they are equipped with built-in sensors that can provide insight into how often and how long drivers use their phones and what they use them for. Telematics data show patterns comparable to the National Highway Traffic Safety Administration's (NHTSA's) annual roadside National Occupant Protection Use Survey (NOPUS) findings of driver electronic device use (Reagan et al., 2024), and offer some advantages to roadside observations. The information from telematics is more nuanced, as it records phone use while the vehicle is in motion and at all times of day, while roadside observations are only recorded when vehicles are stopped and during daytime hours (NCSA, 2024b). Telematics also offers access to a large sample of drivers. CMT's technology is used in opt-in safe driving mobile apps; Safest Driver and RoadClub are examples of publicly accessible options.

The overarching goal of this study was to determine whether telematics can offer concrete evidence of underreporting. To do that, we explored the number of crashes in which a telematics-enrolled driver was recorded as using a cellphone prior to a crash who was not classified as using a cellphone in police crash reports.

2. METHOD

The Insurance Institute for Highway Safety (IIHS) and CMT collaborated on this study, which piloted the feasibility of linking telematics- and police-report-based datasets to compare how the two sources record phone use. CMT is a large telematics services provider. Their artificial intelligence-driven technology uses mobile phone sensors and other devices to detect risky driving behaviors like hard braking, speeding, and harsh acceleration and then provides feedback to improve driver behavior (CMT, 2023). It also detects crashes and can notify emergency services if a driver is unable to call for help. When a CMT-based application is installed on a mobile phone, CMT can measure the amount of time drivers spend using their phones during a trip and distinguish to an extent how they are using their device. The company can identify when the user is making calls, manipulating the phone, and when the screen is active for an application like navigation, but it cannot determine what specific apps are being used. CMT also uses machine learning and historical trip data to classify a user as a driver or passenger (Park, 2022), allowing us to limit our analysis to smartphone use by drivers.

Modern smartphones make it possible to detect when a call is in progress. CMT's platform classifies a driver's phone use based on audio transmission and unlocked screen interactions. Calls are deemed handheld if audio is transmitted with the handset and hands-free if audio is transmitted with the smartphone's loudspeaker, vehicle's Bluetooth, or integrated infotainment system. The platform identifies "manipulation" as when a driver actively interacts with an unlocked screen (e.g., typing, gaming, scrolling, swiping, holding). It marks "passive use" when the screen is unlocked but not interacted with (e.g., mounted GPS navigation, streaming video). As such, the four categories of phone use we identified for comparison were handheld calls, hands-free calls, manipulation, and passive use.

CMT also uses the device’s built-in sensors to detect a likely crash, which is defined as one or more impacts between a vehicle and one or more objects (e.g., another vehicle, stationary object, pedestrian) (Shea et al., 2019). Crashes are considered likely after one or more sudden changes in GPS speeds and longitudinal, lateral, or vertical acceleration of set thresholds, and when the GPS speed

converges to zero within a set timeframe after the start of the detected crash event. Potential events are excluded as crashes if they are detected shortly after the trip starts, because the GPS has a high chance of reporting speed errors in those instances.

The crash detection capability used in this study represents an experimental methodology not previously employed in published research. Phone use detection is integrated within the same crash detection tool set, and as such operates differently from the methodology underlying CMT's standard published distraction statistics. Because this methodology and its underlying platform has not appeared in prior publications that use CMT risk analysis, phone use figures reported here should not be compared directly with CMT's published distraction rates and should be understood as outputs of this unique approach. Additionally, CMT's operational distraction metric, the measure used in its published reports and driver scoring programs, covers active phone interaction only: handheld calls, hands-free calls, and unlocked screen manipulation. For this study, IIHS included passive phone use as defined above because drivers are using smartphones in this way (Cox et al., 2023) and because passive use can divert a driver's eyes from the forward roadway to the phone. Though glance duration during passive use is unknown and likely varies based on the type of content displayed (navigation vs. streaming video), this limitation does not change the underlying safety concern: crash risk is associated with the length of time the driver's eyes are not on the road, regardless of why the driver is looking away (Klauer et al., 2006).

2.1 Datasets

IIHS compiled publicly available police-reported crash data from Connecticut, Illinois, Ohio and Texas from January 1, 2021, through December 31, 2023, or early April 2024, depending on the state. We limited this study to single- and two-vehicle crashes of all severities, resulting in a sample of approximately 3 million crashes. Only variables necessary for the matching process were shared with CMT. This excluded at-fault information and any details that could be used to identify the driver.

CMT compiled a dataset of crashes detected by its telematics technology among smartphone enrollees in the four study states over the study period. It identified instances when handheld calls, hands-

free calls, manipulation, and passive use were recorded within 30-second and 10-second increments before the crash was detected.

2.1.2 Data privacy

To maintain the privacy of its telematics users, CMT linked the crash data and conducted the analysis and shared the aggregate results with IIHS. The methodology was designed such that it is not possible to disaggregate the results in any way that would identify an individual driver or crash. No personally identifiable information and no variables beyond those discussed in the paper were shared with IIHS at any stage of this research.

2.1.3 Linking and analysis

Crash date, crash time, latitude, and longitude were used to match police-reported crashes to those identified by CMT. To link the datasets, CMT converted the local time of the crash on the police report to Coordinated Universal Time (UTC) time and matched the locations by latitude and longitude. To optimize matching while accounting for discrepancies in time and location variables, crashes were considered a match if the police report indicated the crash happened within a 15-minute window and 1,500-meter (0.93-mile) radius of the crash location and time as identified by CMT.

We assumed time and location measures were more accurate in CMT's data because telematics technology records the time and location at impact, while this information is subject to inaccuracies in police reports (Imprialou & Quddus, 2019; Iqbal et al., 2020; Sarasua et al., 2008). For example, if the time on the police report was converted to 1:15 UTC and CMT detected a crash at that location at 1:11 UTC, we looked at the time difference between distraction events and 1:11 UTC.

Table 1 shows how CMT matched the distraction values on police reports to the four types of cellphone uses it can detect. If an enrolled driver engaged in more than one phone-based behavior 30 seconds before the crash, only the most recent behavior before the crash was counted and compared with the police crash report. We first matched the two datasets at the crash level, but in the rare event that both

drivers in a two-vehicle crash were enrolled users and used their devices in the 30 seconds prior to the incident, both uses were logged and compared with the police-crash data. That means for the two-vehicle crashes, the maximum number of cellphone uses that could be recorded (two per crash) was higher than the number of linked crashes. We classified the two datasets as in agreement if the police report showed the same type of cellphone use as the telematics data (i.e., both showed manipulation) but not if they showed uses of two different types (e.g., passive use in the telematics data and manipulation in the police report). Accuracy in identifying the particular cellphone behavior is important because some states permit certain phone-based tasks but not others, allowing handheld calls but prohibiting texting, for example. If banned activities are often mistaken for permitted ones, that could exacerbate the problem of underreporting.

3. RESULTS

There were 1,543 single-vehicle crashes linked between the two datasets (Table 2). Among these, CMT identified phone use during the 30 seconds before the crash in 7% of crashes and phone use during the 10 seconds before the crash in 4%. For both time intervals, the most common use category was passive use, followed by manipulation. Within 10 seconds of their crashes, passive use was recorded for 40 drivers and manipulation was recorded for 23 drivers. CMT showed six drivers talking on the phone (three handheld, three hands-free) in the 30 seconds before they crashed. In the same set of linked crashes, police crash data indicated one driver was on a handheld call, three drivers were manipulating their phones, and five were passively using them, for a combined phone use rate of 0.6%. The two datasets agreed on the type of distraction (phone manipulation) for only one crash. That driver manipulated their phone 24 seconds before CMT recorded the crash event.

Table 3 shows phone use as recorded by CMT and distraction as reported by police for 15,301 linked two-vehicle crashes. As with the single-vehicle crashes, manipulation and passive phone use were the most common behaviors recorded by CMT. However, while passive use was still most common 10 seconds before these crashes, manipulation was more common than passive use in the 30 seconds before

impact. CMT detected phone use of any kind within 10 seconds of 5% of detected crashes and within 30 seconds of 8% of detected crashes. Police crash reports coded any phone use by a driver in 0.3% of these linked crashes, recording manipulation most often (17 crashes) followed by passive use (15 crashes). All the crashes in which police noted cellphone use of any kind were also recorded as including cellphone use by CMT. However, the two datasets agreed with each other on type of phone use in two crashes (a driver in one crash manipulated their phone 10 seconds prior and a driver in the second crash passively used their phone one second prior to CMT's crash detection).

4. DISCUSSION

This study demonstrated the novel ability to link crash data from police crash reports with telematics data, which allowed us to compare recorded cellphone use from both sources for the same crash. Examining nearly 17,000 linked crashes, we compared the prevalence of cellphone use at two different time intervals within a 30 second window prior to crashes among telematics users with data from police reports. The telematics data showed that phone calls were rare while manipulation of unlocked devices was more common, in line with what NHTSA's annual roadside survey has shown (NCSA, 2024b). Police crash reports in this sample coded cellphone distractions for less than 1% of both single- and two-vehicle crashes, slightly lower than NHTSA's annual estimates of cellphone-affected crashes during the study period (NCSA, 2023, 2024a, 2026), while the telematics data showed cellphone use occurred less than 30 seconds before 7%–8% of the linked crashes. Agreement between the two datasets was virtually nonexistent at the study's outer bounds of 30 seconds.

We explored phone use at the largest interval of 30 seconds because the average phone distraction lasts 23 seconds (Madden et al., 2020) and because the distraction hangover phenomenon suggests driving performance continues to be affected for a period after phone use has ended. The driving performance degradation may continue after the distraction ends because it takes time to disengage from a secondary task and reengage with the driving task (Strayer et al., 2015) and because drivers may take their eyes off the forward roadway when putting their phone down after using it (Madden et al., 2020). Snider et al.

(2023) found drivers in a simulator exhibited performance degradation lasting up to 25 seconds after a phone-based distraction. Similarly, CMT reported an 82% increase in hard braking 10 seconds after phone interaction ends (Madden et al., 2020). This hangover effect is not restricted to mobile phones, as it took drivers an average of 27 seconds to reengage with the driving task after interacting with in-vehicle information systems (Strayer et al., 2015).

This study found that passive phone use was the most common way drivers used their phones in the 10 seconds prior to a crash in both single- and two-vehicle crashes, though it is unknown how long this type of phone use takes a driver's eyes off the road or what apps were used. It is likely that some drivers captured in this category could have been displaying navigation, a safer alternative to printed paper maps (Dingus, 2014), since Cox et al. (2023) found it to be the most common way drivers use smartphones in a 2022 survey. Short glances of 2 seconds or less away from the forward roadway are not associated with increased near crash or crash risk (Klauer et al., 2006). However, streaming content, which one in four drivers admitted to doing when surveyed in 2022 (Cox et al., 2023), would also fall under this use category and could cause longer glances away from the forward roadway. When Klauer et al. (2006) analyzed glance location and event type, long glances in the direction of a vehicle's center mirror and center stack—a common location for drivers to install external phone mounts—were most strongly associated with crashes and near crashes. Since many states permit hands-free use of devices, officers may be less likely to record unlocked phone use without interaction on the police report, though field options of "other activity with an electronic device" and "other electronic device—navigation, radio, etc." exist (see Table 1).

The findings that cellphone use occurred within 10 seconds of 4%–5% of crashes and within 30 seconds of 7%–8% crashes complement the Blincoe et al. (2023) estimates that cellphone distractions may contribute to as many as 6.1% of all crashes. The primary visual-manual phone distractions when the SHRP2 data were collected were likely limited to dialing and typing or reading text messages (Dingus et al., 2016), but drivers are now using voice commands for those tasks and have found other ways to

communicate since then (Cox et al., 2023), and other demanding visual-manual tasks are presenting new distractions for drivers. While built-in text messaging apps did not make the top ten most used applications in a CMT survey of U.S. drivers (CMT, 2025a)—Facebook's Messenger came in fifth, behind Google, Gmail, the default camera app, and Facebook—the problem of distraction remains severe.

While handheld calls and manual texting using build-in apps have decreased, we have seen a rise in manipulation, a riskier type of phone use, over the last decade (NCSA, 2024b). Although hands-free calls are not reflected in our study as the most common cellphone task in the 30 seconds prior to a crash, telematics data indicate that is the cellphone activity that drivers spend the most time on per hour (CMT, 2024, 2025b), suggesting drivers may have also replaced handheld calls with hands-free calls over time. However, the prevalence of hands-free calls has been fairly steady in NOPUS data and is lower than that of handheld calls and manipulation (NCSA, 2024b). This behavior may be difficult for a roadside observer to positively identify because NOPUS methodology requires a headset to be visible, so drivers making hands-free calls using their vehicle's Bluetooth or other integrated system would be excluded.

Several limitations should be noted. We were only able to include crashes within CMT's cellphone program database, so drivers without CMT's telematics software on their phones were naturally excluded. According to CMT, all demographics are well-represented in their programs, but white people and more affluent households are slightly more common among their users than in the general population. CMT acknowledges drivers who think they are "good" drivers may be more likely to self-select into these programs. A potential for survivor bias also exists because some drivers may improve their behavior based on the feedback received from the program while others who receive poor driving feedback may remove the app. This means the CMT sample may exclude drivers who engage in riskier driving behaviors and are therefore more likely to be involved in a crash, resulting in fewer crashes linked overall and fewer where cellphone distractions could have been a factor.

CMT uses machine-learning models to infer that the user is driving a motor vehicle but provides users with an option to label a trip as one in which they were a passenger and to indicate instances in

which the driver's phone was used by a passenger. It is possible that some phone use recorded in the study window prior to the crash as being done by the driver was done by passengers, but those cases are likely minimal as Ebert et al. (2024) found the platform's overall accuracy of driver vs. non-driver classification was over 96%. Older phones and phones in low-power mode were found to have slightly lower accuracy.

This study was limited to crashes reported to police in the study states. About 53% of all crashes and 60% of property-damage-only crashes are estimated to go unreported to police (Blincoe et al., 2023). Each of the four study states has some type of cellphone distracted driving law (IIHS, 2025a). While this study considers how the threat of legal consequences might prevent a driver from admitting to police that they were using their phone before a crash, it is also possible that the same fear might dissuade drivers from reporting a cellphone-related crash at all, especially if no other parties were involved. While this study shows the degree to which police crash reports can underestimate driver cellphone use, the true proportion of cellphone-affected crashes is likely greater still because so many crashes are unreported. Though it cannot be compared with the current study, CMT crash data, which are free from this reporting limitation, found 34% of crashes happen within a minute of cellphone distractions (CMT, 2024).

Notably, this study's findings differ from other distraction estimates published by CMT because the current study does not use CMT's operational definition of distraction. If we restricted this analysis to CMT's standard definition (which includes handheld calls, hands-free calls, and unlocked screen manipulation but not passive use), however, the results would still demonstrate cellphone distractions are underreported in police crash data, as telematics identified active phone use within 10 seconds of 2%–3% of crashes, versus less than 1% in police crash data.

Some identical crashes may not have been linked because the difference in the CMT and police-report data was greater than the 15-minute and 1,500-meter radius we used to link crashes. It is also possible that because of the distance radius used, crashes that were not true matches were erroneously considered as such, though the likelihood of multiple police-reported crashes within a 15-minute window and 1,500-meter radius seems low. Crash time is often estimated on witness statements so they can lack

minute-level accuracy (Golob & Recker, 2003). Many states now use GPS technology to record crash location, which could improve accuracy over older approaches like using measurements to reference points or cross streets (Iqbal et al., 2020). However, many states have driver removal laws that require drivers involved in minor crashes to move their vehicles from travel lanes to prevent blocking traffic (Federal Highway Administration, 2020), so it may still be difficult for a responding officer to determine the exact crash location even with a GPS device.

We looked at single-vehicle and two-vehicle crashes separately because we did not know which driver in a two-vehicle crash had CMT's mobile technology. However, the percentage of cellphone behaviors identified in CMT's data are very similar in single- and two-vehicle crashes. It is also worth noting that we did not explore which drivers were cited as being at-fault, so the results reported should not be interpreted as directly causal. Finally, this study does not quantify how much distraction from all sources is underreported by police, which is widely believed to occur for the same reasons that cellphone distractions are underreported (Blincoe et al., 2023; NCSA, 2026). It is possible that some of the telematics-detected phone use was improperly reported by police as "generally distracted" or "lost in thought (daydreaming)", which are the most common types of distraction listed and account for two-thirds of the types of distraction recorded in crash reports in fatality data (IIHS, 2025b). This would not result in a match between datasets but could be explored in further detail using similar methodology in the future.

5. CONCLUSION

Safety researchers have long theorized that phone use is underreported as a crash contributor in police-reported crash data. This study provides evidence that suggests phone use may be a factor in at least 7 times the number of crashes that are reflected in police crash data. Agencies which assemble/disseminate police-reported crash data (or rely on their analyses for decision-making) should acknowledge these shortcomings. This pioneering approach was made possible by an experimental crash

detection platform integrated within CMT's mobile technology and provides a cost-effective alternative to traditional naturalistic study designs.

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7. TABLES

Table 1

Coding of police-reported behaviors

CMT categorization	Police report value
No phone use	Not distracted
	Other/unknown
	Unknown if distracted
	Unknown
	Unk
	N/A
	Passenger
	Other distraction outside the vehicle
	Driver inattention
	Outside the vehicle (includes unspecified external distractions)
	Other distraction inside the vehicle
	Other distraction inside the vehicle (eating, personal hygiene, etc.)
	Distraction in vehicle
	Other—inside vehicle
	Inattentive/daydreaming
	Other—outside vehicle
Passive phone use	Other activity, electronic device
	Other activity with an electronic device
	Other electronic device—navigation, radio, etc.
	Cell/mobile device use—unknown
Handheld call	Talking on handheld electronic device
	Cell/mobile device use—talking
	Talking on handheld communication device
	Cellphone handheld
Manipulation	Manually operating an electronic communication device (texting; typing; dialing)
	Cell/mobile device use—texting
	Cellphone—texting, email, etc.
Hands-free call	Talking on hands-free communication device
	Talking on hands-free electronic device
	Cellphone hands-free

Table 2

Instances of cellphone use captured by telematics and police reports in 1,543 linked single-vehicle crashes

	Cellphone use categories					
	Handheld calls	Hands-free calls	Manipulation	Passive use	No phone use	Total phone behaviors (%)
Telematics recorded: 10 seconds	2	0	23	40	1,478	65 (4%)
Telematics recorded: 30 seconds	3	3	49	52	1,436	107 (7%)
Police recorded	1	0	3	5	1,534	9 (0.6%)
Agreement within 30 seconds	0	0	1 [a]	0		1

[a] Detected 24 seconds prior to the recorded crash.

Table 3

Instances of cellphone use captured by telematics and police reports in 15,301 linked two-vehicle crashes.

	Cellphone use categories					
	Handheld calls	Hands-free calls	Manipulation	Passive use	No phone use	Total phone behaviors (%)
Telematics recorded: 10 seconds	14	53	287	337	14,645	691 (5%)
Telematics recorded: 30 seconds	19	87	590	534	14,121	1,230 (8%)
Police recorded	6	1	17	15	15,292	39 (0.3%)
Agreement within 30 seconds	0	0	1 [a]	1 [b]		2

Note. Telematics data captured and recorded behaviors of both drivers when both were CMT users.

[a] Detected 10 seconds prior to the recorded crashes.

[b] Detected 1 second prior to the recorded crash.

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