Support for legislative, technological, and organizational strategies to reduce cellphone use while driving: Psychological predictors and influences of language

Brittany Shoots-Reinhard\textsuperscript{a,b}, Hayley Svensson\textsuperscript{a,c}, and Ellen Peters\textsuperscript{b}

\textsuperscript{a}Department of Psychology, The Ohio State University, Columbus, Ohio; \textsuperscript{b}Center for Science Communication Research, School of Journalism and Communication, University of Oregon, Eugene, Oregon; \textsuperscript{c}Department of Psychology, Rutgers University, Piscataway, New Jersey

\textbf{ABSTRACT}

\textbf{Objective:} A large body of research has established that cellphone use while driving (CUWD) is common and dangerous. However, little research has been conducted about how people react psychologically to various distraction-reduction strategies and, ultimately, support or do not support them. Understanding support for reduction is important for predicting use of technological solutions and compliance with laws and for improving communication and education about the risks of CUWD.

\textbf{Methods:} We measured support for a variety of legislative, technological, and organizational strategies to reduce CUWD in an online sample of American drivers ($N=648$). We also developed evidence-based communication techniques, describing strategies in terms of benefits vs. costs or using freedom-invoking vs. freedom-reducing language to assess what would influence support.

\textbf{Results:} Support for CUWD reduction was generally high. It was predicted by driver characteristics and beliefs. For example, drivers who supported reducing CUWD more also had lower CUWD reactance, greater anti-CUWD beliefs, higher personal risk perceptions of CUWD, and greater self-reported distracted driving. Age and perceived ability to drive distracted did not predict overall support. However, two strategies that allow for handsfree phone use were supported more by people who engaged in more CUWD, perceived they had greater ability to CUWD, perceived more benefits to CUWD, had more positive affect to cellphones, and were younger. Communication techniques also influenced support. Specifically, the same strategy was supported more when described using benefits and permissive language instead of costs and restrictive language.

\textbf{Conclusions:} Most respondents supported strategies to reduce CUWD, and beliefs about risks and benefits predicted this support. Reactance to CUWD messaging emerged as a key predictor of lower support (and of greater self-reported distracted driving), indicating that it could be an important variable to consider when designing strategies to reduce CUWD. When targeting people resistant to quitting CUWD entirely, communicators could recommend a switch to handsfree use. Communicators who emphasize benefits and use permissive language also may increase support for CUWD reduction.

\textbf{Introduction}

\textbf{Distracted driving prevalence and risks}

Considerable research has demonstrated the risks of cellphone use while driving (CUWD) (e.g., Caird et al. 2018; Dingus et al. 2016). These risks include slower reaction times and more variable speed, lane position (i.e., weaving), and following distance, which ultimately lead to more and more severe collisions (e.g., Overton et al. 2015). In 2018 alone, at least 2,841 Americans were killed in distraction-related crashes (National Center for Statistics and Analysis 2019).

\textbf{Predictors of public support for limiting CUWD}

Various strategies have been used to change driving behavior, including legislation, public communication campaigns, and road design interventions (see Richard et al. 2018 for a review). In the United States, most states have restricted cellphone use for texting and handheld reasons, and handheld bans in particular are associated with the lowest rate of fatal crashes. Little is known, however, about how people react psychologically to distraction-reduction strategies and, ultimately, whether they support them, the focus of the present paper. Understanding the psychological mechanisms driving support is important for several key reasons. First, drivers are more likely to comply with laws they support (e.g., Tapp et al. 2015). Second, understanding what drives support for reducing distracted driving can suggest better methods for communicating about risk and strategies to change driver behavior. For example, if support is lower among people who think CUWD poses little risk, education about its risks could reduce CUWD and increase support.
for restriction. Third, these mechanisms can direct strategies. For example, people who feel that CUWD is beneficial may be unwilling to turn off notifications but open to handsfree use. People may choose different risk-mitigation strategies, and this freedom of choice ultimately may save lives. Fourth, understanding mechanisms driving support for distraction-reduction strategies may point to similar domains where researchers have already identified effective strategies that could be tested within distracted driving. Finally, public support impacts policy (Burstein 2003). Thus, legislative solutions supported by a larger share of the public may be more likely to become policy.

**Possible demographic and psychological variables underlying support for distraction-reduction strategies**

The purpose of the current investigation was to uncover distraction-reduction strategies viewed favorably by drivers and determine what predicts support for them, including demographics and psychological variables. Support for laws tends to be higher among women, older drivers, drivers who lived in a state with such a law, and drivers who reported less distracted behaviors (e.g., Delgado et al. 2018; Schroeder et al. 2018). Unclear from this research was whether demographics or distracted behavior are independent predictors of support for distraction reduction, as male and/or younger drivers report riskier behaviors (e.g., Delhomme et al. 2009). Also unclear are whether beliefs drive attitudes toward distraction-reduction strategies and whether those attitudes might be explained by demographics or the extent of distracted behavior.

Furthermore, little research has examined support for restricting cellphone use while driving as a function of psychological variables. Sanbonmatsu and colleagues, however, found that college students who supported (vs. did not support) legislative action restricting CUWD reported greater perceived risks and lower benefits of CUWD, and lower perceived ability to use cellphones safely while driving (Sanbonmatsu et al. 2016). In general, people who perceive dangerous driving behaviors as riskier and/or less beneficial tend to report lower engagement in them (e.g., Weller et al. 2013). People also may feel that risks of CUWD do not apply to them personally; such thinking relates to lower crash risk estimates for themselves vs. others and greater dangerous driving behaviors (e.g., Delhomme et al. 2009).

Information about how other people act and what they approve (i.e., social norms) often predict behavior (e.g., Ajzen 1991), including driving behavior (e.g., Shevlin and Goodwin 2019). Reactance—a pattern of negative affective and cognitive responses to messages perceived as restricting recipients’ freedom—results in increased message rejection and decreased intentions to follow recommendations (e.g., Dillard and Shen 2005). Neither reactance nor norms have been examined as predictors of support for distraction-reduction strategies. Thus we predicted:

Hypothesis 1: Support for distraction-reduction would be higher among drivers with lower self-reported distracted driving, greater risk perceptions, lower benefit perceptions, greater perceived ability to drive distracted, greater perceived prevalence of distracted driving, and lower reactance.

**Altering public support through the language used to describe strategies**

How policies or strategies are communicated also can influence support for them (i.e., “framing”). People prefer products described in ways that focus on positive vs. negative attributes (e.g., Levin et al. 1998). For example, meat described as “75% lean” was rated as higher in quality than meat described as “25% fat.” Strategies, such as insurance discounts for safe drivers, can also be framed in terms of benefits (e.g., “safe drivers pay less”) or costs (e.g., “unsafe drivers pay more”). Focusing on benefits appears particularly effective for preventive behaviors, like safe driving (e.g., Gallagher and Updegraff 2012). People also tend to react more positively to permissive language (e.g., “can,” “consider”) than restrictive language (e.g., “should,” “must”; Carpenter 2013). Strategies can be described either way (e.g., apps can “help you drive without using your phone” vs. “prevent you from using your phone.”). We expected:

Hypothesis 2: A strategy framed in positive or permissive terms would receive greater support than the same strategy framed in negative or restrictive terms.

**Present survey and experiment**

Here, we focused primarily on understanding the psychology of support for distraction-reduction strategies, for which little published research exists. Existing studies relied on small samples (N < 250) from restricted geographical regions, mostly focused on young drivers (e.g., Delgado et al. 2018), or did not analyze psychological predictors (e.g., Schroeder et al. 2018). The current research contributes to the existing literature by surveying a more diverse and larger sample, asking about a greater variety of strategies, and investigating possible mechanisms for support for use in developing more effective anti-CUWD interventions. We assessed risk and benefit perceptions of CUWD, perceived prevalence of CUWD, relative driving ability, reactance, self-reported CUWD, and support for CUWD reduction in a large national online sample. We also manipulated (within-participant) the language used to describe distraction-reduction strategies.

**Method**

Additional references appear in the Appendix (see online supplement).

**Sample and procedure**

Participants were 648 American drivers recruited online via Cloud Research (Turk Prime at the time of data collection). These samples provide reliable, valid data, but are not
representative (Appendix A). Participants were informed about the survey before choosing to continue; Ohio State University IRB waived documentation of consent due to minimal risk (Protocol 2010B0458). Participants were screened from a baseline survey; only participants with driver's licenses and who drove at least 3 days per week were eligible. The sample was 50% female, 78% white, and 18 to 79 years old (Mdn = 36.0, Mean(SD)=39.5 (11.76)).

In a 25-minute baseline survey completed online, participants self-reported distracted driving behaviors and demographics. The second 20-minute online session several months later measured driving attitudes and beliefs and additional measures not examined here (see Appendix A). Both sessions were structured so that participants could not change prior responses. Participants were paid $4.50 ($2.50 initially and $2 for the second session).

**Measures**

**Self-reported distracted driving**

Participants were asked about 13 behaviors (e.g., changing volume using dashboard, holding phone conversations, etc.) and CUWD in fourteen situations (e.g., during the day, at night, etc.). We modeled our items on the Distracted Driving Exposure scale (Bergmark et al. 2016) but used a numeric response scale to reduce differences in interpreting verbal likelihood scales (e.g., Windschitl and Wells 1996). Participants responded on a scale from 0% to 100% of trips. Items were averaged. Higher scores indicated greater distracted driving (Cronbach’s $\alpha = .94$).

**Perceived prevalence of CUWD**

Participants estimated the percentage of trips the average driver performed thirteen distracted driving behaviors while driving (e.g., “While driving, how often does the average driver hold phone conversations?”) using sliding scale from 0% to 100% of trips. Estimates were averaged; higher scores indicated greater prevalence (Cronbach’s $\alpha = .94$).

**Relative ability**

Participants assessed their driving ability relative to other people using percentile scores on a sliding scale “where 0 means everyone is better than you... and 100 means you are better than everyone else.” We also asked about relative crash risk using cellphones compared to other drivers. Higher scores indicated higher perceived ability relative to others.

**Risk and benefit perceptions**

Participants reported perceptions of three risks and then three benefits for themselves of talking on the phone, texting, and using navigation or GPS while driving on seven-point response scales (1 = not at all risky/beneficial to 7 = extremely risky/beneficial). Items were averaged to form indices of risk and benefit perceptions. Higher numbers indicated greater risk (Cronbach’s $\alpha = .75$) and benefit (Cronbach’s $\alpha = .64$).

**Anti-CUWD beliefs**

A 16-item scale assessed the risk and appropriateness of CUWD for other people (e.g., “People who use cell phones while driving are acting irresponsibly”) (Weller et al. 2013). Higher scores indicated greater anti-CUWD beliefs (Cronbach’s $\alpha = .91$).

**Reactance to warnings**

We developed a reactance scale modified from tobacco warning label studies (Hall et al. 2018). Participants answered six questions about beliefs that risks were exaggerated and anger toward messaging (e.g., “Warnings about distracted driving are trying to manipulate me”) using five-point response scales (1 = strongly disagree to 5 = strongly agree.). Items were averaged; higher scores indicated greater reactance (Cronbach’s $\alpha = .91$).

**Support for distraction-reduction strategies**

We asked about nineteen different strategies (Table A2) to reduce distracted driving: technological (e.g., apps or settings), educational (e.g., educational programs), organizational (e.g., insurance discounts), and legislative (e.g., distracted-driving fines). Participants rated their level of support for each strategy in random order on six-point scales from 1 = strongly opposed to 6 = strongly in favor. Higher scores indicated greater support. Embedded within the nineteen strategies were four pairs of strategies (described below) that comprised experimental manipulations of the language used to describe distraction-reduction strategies (averaging the pairs vs. using them as separate items does not change results). Unexpectedly, support for strategies that facilitated handsfree use of devices while driving (i.e., Bluetooth and apps that allow people to receive and respond to messages using voice-to-text) were weakly to negatively correlated with the other strategies but positively correlated with each other ($r = .41$). Thus, we excluded them from the index of CUWD reduction and, instead, averaged them for a separate index of handsfree use (Appendix B). The remaining seventeen items were combined into an index of overall support for distraction-reduction strategies (Cronbach’s $\alpha = .91$).

**Embedded experiments on support for distraction-reduction strategies**

For four strategies embedded in the measure of distraction-reduction support, participants responded twice to the same strategy described with different language (Table 4). In the first pair, insurance discounts were described in a positive frame (“charging good drivers less”) or negative frame (“charging bad drivers more”). For the remaining comparisons, we created descriptions that varied in how permissive or restrictive they were described. For example, we tested whether apps or settings that “help you drive without using your phone” (permissive) would produce more support than those that “prevent you from using your phone” (restrictive).
Data analysis strategy

We first analyzed mean levels of support for each strategy and correlations between them. Next, we predicted overall support for distraction-reduction strategies (i.e., the 17 positively correlated items) from psychological variables using multiple regression, with covariates including age, race, gender, and driving amount. We reported unstandardized coefficients, which are in the scale of the original variables, and standardized coefficients, which can be used to compare the relative predictive power of variables within an analysis. Finally, we tested experimental language manipulations using within-subjects t-tests.

Results

General findings

Descriptive statistics appear in Table 1. Overall, respondents supported methods of reducing distracted driving (Table 2), and support declined as strategies became more restrictive (Appendix C).

Psychological predictors of support for distraction-reduction strategies

Partly consistent with H1, support for distraction reduction was higher among participants who reported greater perceived risk, \( b(\text{se}) = 0.12 (0.03), p < .001, \) less reactance, \( b(\text{se}) = -0.14 (0.04), p < .001, \) and more anti-CUWD beliefs, \( b(\text{se}) = 0.29 (0.05), p < .001. \) Interestingly, although the simple correlation was negative (Table A4), regression analyses revealed that those reporting more distraction indicated greater support for strategies that reduce distraction, \( b(\text{se}) = 0.01 (0.002), p = .011 \) (Table 3, Appendix D). Relative CUWD ability and benefit perceptions did not predict support.

Experimental effects of language used to describe strategy

H2 was generally supported. Participants indicated greater support for insurance discounts mentioning benefits (i.e., “charge good drivers less”) \( M = 4.33, SD = 1.41 \) than equivalent costs: “charge poor drivers more” \( M = 4.06, SD = 1.50, t (647) = 6.43, p < .001. \) Second, they supported benefits-focused and less restrictive descriptions of apps or settings that “help you drive without using your phone” \( M = 4.58, SD = 1.10 \) more than those that “prevent you

| Table 1. Descriptive statistics. |
|-------------------------------|
| **Mean (SD)** | **Range** | **Cronbach’s \( x \)** |
| Support for distraction reduction (17 items) | 4.31 (0.83) | 1.65–6.00 | .91 |
| Support for handsfree CUWD (2 items) | 4.34 (1.05) | 1.00–6.00 | |
| Self-reported distracted driving | 17.30 (15.42) | 0.00–73.33 | .94 |
| CUWD relative ability percentile | 46.86 (23.68) | 0.00–100.00 | |
| Verbal benefit perceptions | 2.95 (1.13) | 1.00–7.00 | .64 |
| Verbal risk perceptions | 5.17 (1.24) | 1.00–7.00 | .75 |
| Anti-CUWD belief scale | 5.89 (0.82) | 2.44–7.00 | .91 |
| Reactance to warnings | 2.02 (1.03) | 1.00–6.33 | .91 |
| Driving amount (hours/week) | 6.80 (6.06) | 0.20–50.00 | |

Means with standard deviations, ranges, and Cronbach’s \( x \) are reported where relevant. Additional variables are reported in Table A3. Correlations appear in Table A4.

| Table 2. Average support for programs, policies, and technology to reduce distracted driving. |
|-----------------------------------------------|
| **Are you in favor of or opposed to ________?** | **M (SD)** | **In favor** |
| 1. Insurance discounts or plans for safe drivers | 5.31 (0.89) | 96% |
| 2. Educational programs targeted at teen drivers | 5.21 (0.90) | 96% |
| 3. Technology that assists parents in teaching teen drivers | 4.96 (1.02) | 94% |
| 4. Organizational (e.g., school or workplace) pledges to not drive distracted | 4.68 (1.16) | 87% |
| 5. Organizational (e.g., school or workplace) bans on cell phone use | 4.55 (1.32) | 80% |
| 6. Eye tracking technology in your car that warns you when you’re distracted | 3.82 (1.47) | 63% |
| 7. Technology to read messages aloud but not respond | 3.79 (1.41) | 62% |
| 8. Steering wheel sensors that warn you to keep both hands on the steering wheel | 3.39 (1.56) | 48% |
| 9. Technology that pulls your car over if it detects you are distracted | 3.21 (1.57) | 43% |

Participants rated their support on a scale from 1 (strongly opposed) to 6 (strongly in favor). Strategies are ordered from most to least supported. Items used in the within-participants experiment are included in Table 4; the index of support for distraction reduction included all the items here and in Table 4. The full wording of item 7 appears in Table A2. Two items that measured support for strategies that facilitated handsfree use of devices while driving (i.e., Bluetooth and apps that allow people to receive and respond to messages using voice-to-text) were included in a separate index of handsfree use (Appendix B).

| Table 3. Regression model predicting support for CUWD reduction strategies. |
|-----------------------------|
| **B (se)** | **\( \beta \)** | **p** | **VIF** |
| (Constant) | 2.28 (0.39) | | <.001 |
| CUWD relative ability percentile | 0.00 (0.00) | -0.03 | .442 | 1.34 |
| Self-reported distracted driving | 0.01 (0.00) | .11 | <.001 | 1.45 |
| Anti-CUWD beliefs | 0.29 (0.05) | .29 | <.001 | 2.16 |
| Verbal risk perceptions | 0.11 (0.03) | .17 | <.001 | 1.62 |
| Verbal benefit perceptions | -0.01 (0.03) | -.01 | .760 | 1.75 |
| Reactance to warnings | -0.14 (0.04) | -.17 | <.001 | 1.76 |

Unstandardized B-coefficients with standard errors in parentheses and standardized \( \beta \)-s are both reported, along with variance inflation factors (VIF). For gender, 0 = male, 1 = female. For race, 1 = non-Hispanic white, 0 = non-white. All other variables were continuous. Model fit is \( F(10,633) = 22.89, p < .001. \) Adjusted \( R^2 = .26. \) Age, gender, race, and driving amount were included as covariates but omitted from this table (none were significant predictors).
Table 4. Support for programs, policies, and technology to reduce distracted driving depending on language used to describe strategy.

| Are you in favor of or opposed to | M (SD) | In favor |
|----------------------------------|--------|----------|
| 1a. Legislation and laws that punish people who use their cell phones while driving with fines | 4.59 (1.25) | 83% |
| 1b. Legislation and laws that ban cell phone use while driving | 4.39 (1.36) | 76% |
| 2a. Apps or settings that help you drive without using your phone | 4.58 (1.10) | 86% |
| 2b. Apps or settings that prevent you from using your phone while driving | 4.15 (1.42) | 70% |
| 3a. Technology that monitors driving ability and evaluates performance | 4.12 (1.33) | 73% |
| 3b. Technology that measures driver behavior patterns and coaches driving ability | 4.07 (1.27) | 73% |
| 4a. Insurance programs that ... charge good drivers less | 4.33 (1.41) | 77% |
| 4b. Insurance programs that ... charge poor drivers more | 4.06 (1.50) | 69% |

Participants rated their support on a scale from 1 (strongly opposed) to 6 (strongly in favor). Pairs of strategies are indicated with a and b and are ordered from most to least supported by the most supported of the pair.

Discussion

Our sample of American drivers supported strategies to reduce CUWD. However, effective measures did not necessarily receive more support. Educational programs and technology for teaching teens received high support and can be effective (e.g., Curry et al. 2015). However, organizational pledges have not been shown effective and received more support than handheld bans and laws against CUWD (Richard et al. 2018) and technology that restricts phone use (e.g., Oviedo-Trespalacios et al. 2019). Instead, it appears that more restrictive policies and technologies (or language used to describe them), received less support. Drivers who supported one strategy tended to support other strategies, too. Support for two handsfree strategies, however, was less correlated than that for other strategies; predictors of their support also differed from that for other strategies (Appendix B).

Experimental effects of language on support for distraction reduction

We experimentally tested language eliciting greatest support for distraction-reduction strategies by asking participants to respond to the same strategy twice, using different descriptions. Equivalent policies framed as beneficial (e.g., insurance programs charging good drivers less) received more support than those framed as costly (e.g., insurance programs charging poor drivers more) consistent with prior framing research (e.g., Gallagher and Updegraff 2012). Furthermore, using more restrictive language reduced support for two of three tested strategies. Specifically, laws described as fines were preferred to “bans” as was technology that “help avoid” vs. “prevent” CUWD. However, technology that “measures” and “coaches” was not supported more than the equivalent, restrictive alternative (i.e., “monitors” and “evaluates”). This latter manipulation may have been too weak. Altogether, results suggest that drivers can be induced to support policies more when described in terms of benefits and using less restrictive language. The most empirical support exists for the case of bans vs. fines (Richard et al. 2018). Describing these laws as “handheld bans” is likely counterproductive to increasing acceptance. However, unclear is whether differences in support would translate to durable behavior change (indeed, meta-analyses suggest that framing effects on behavior may be small; e.g., Gallagher and Updegraff 2012).

Individual differences in support for CUWD reduction

As in prior research, support for reduction strategies was higher among older drivers (Schroeder et al. 2018), those reporting less distracted driving (Sanbonmatsu et al. 2016; Delgado et al. 2018; Schroeder et al. 2018), and those with lower risk perceptions, higher benefit perceptions, and greater perceived ability to drive while using cellphones (Sanbonmatsu et al. 2016). Additionally, more reactant participants and those who perceived greater prevalence of CUWD, respectively, reported less and more support for CUWD reduction. Multiple regression analyses indicated that support for reducing CUWD related primarily to lower CUWD reactance and anti-CUWD beliefs, higher personal risk perceptions of CUWD, and greater self-reported distracted driving. Perceived ability, prevalence, and benefit perceptions were correlated with support for CUWD reduction but did not emerge as independent predictors. Restricting to measures with previous empirical support (i.e., education and coaching of teens, cellphone blocking technology, and laws) did not substantially change results (Appendix E).

Having anti-CUWD beliefs was the strongest predictor of support for CUWD reduction (Weller et al. 2013). This measure includes more normative items (e.g., “People who use cell phones while driving are acting irresponsibly”) and more risk-focused questions (e.g., “People who use cell phones while driving are likely to cause an accident”). Thus, targeting norms and risks could be fruitful paths for communications to reduce CUWD, although they could increase reactance. Experimental studies are needed.

We further uncovered reactance as a novel predictor of support for CUWD reduction (and CUWD, Appendix F). It remained a strong independent predictor despite a strong (negative) correlation with anti-CUWD beliefs. These
findings suggest people’s appraisals of the risks (as
being overblown or exaggerated) and anger at messaging
may be important to decisions to drive distracted and sup-
port legislation independent of how much risk they think
their behaviors pose. Reactance may be critically important
for attempts to reduce CUWD with anti-distraction messag-
ing, as reactance to messaging can increase message rejec-
tion and decrease intentions to follow recommendations
(e.g., Dillard and Shen 2005; Hall et al. 2018). Messaging
could avoid forceful language (e.g., Dillard and Shen 2005)
to reduce reactance.

Our findings are consistent with the Theory of Planned
Behavior (e.g., Ajzen 1991) and the Health Belief Model
(Rosenstock 1966), which propose that behavior is a func-
tion of perceptions of the risks and benefits of the behavior.
The Theory of Planned Behavior further specifies ability and
norms as behavioral influences. Like others have found (e.g.,
Shevlin and Goodwin 2019), self-reported distracted driving
was greater among drivers who perceived distraction as
more common, believed they had greater ability than others,
and perceived greater benefits of CUWD (Appendix F).
However, unlike past research on safe driving from a Health
Belief Model approach (e.g., Fernandes et al. 2010), risk per-
ceptions did not predict distracted driving when included in
the model; thus, our results for behavior are more consistent
with the Theory of Planned Behavior. However, support for
CUWD reduction was higher for people with anti-CUWD
beliefs (which includes risk and normative components) and
greater risk perceptions, but perceived ability did not di-
rectly predict support for CUWD reduction; thus, these
results are more consistent with the Health Belief Model.
Critically, both models neglect reactance, a key predictor of
behavior and support for reduction.

Additionally, strategies acceptable to those high in react-
ance could be advocated, such as handsfree technology.
Support for handsfree was higher among drivers who
engaged in CUWD and had more positive affect toward cell-
phones (Appendix B). Because reactance was unrelated to
support for handsfree CUWD, encouraging distracted and
reactant drivers to use handsfree technologies could
reduce crashes.

Limitations

Our sample was more diverse in age and geography than
prior research (Sanbonmatsu et al. 2016; Delgado et al.
2018), albeit non-representative (Appendix A). Our sample
is mainly drivers ages 25 to 44, thus any age effects should
be interpreted with caution. In addition, our use of a non-
representative sample does not preclude possible lower
public support for handsfree phone use and technological
strategies to reduce CUWD. Our findings are also limited by
their correlational nature. The only variable manipulated
was the language used to describe a subset of reduction
strategies. Furthermore, we treated reduction as an outcome
variable, but some variables may have bidirectional effects.
Future research could manipulate variables to confirm causal
relations with support for CUWD reduction. A further
limitation is our self-reported distracted-driving measure.
However, our sample reported greater distraction than other
representative studies (Appendix A), thus attenuating social
desirability concerns. Finally, our exposure measure was lim-
ited in its insensitivity to the danger posed by different
behaviors (texting vs. talking hands-free) and durations
(10 seconds vs. one hour of distracted driving).

To conclude, in a large sample of drivers, those with
greater anti-CUWD beliefs, lower reactance, and greater risk
perceptions supported CUWD reduction more. These varia-les are promising targets for interventions to reduce CUWD. Unfortunately, because greater reactance was associ-
ated with greater distracted driving and lower support for
reduction strategies, persuading the worst offenders to
change behavior will likely be difficult. Nonetheless, less
restrictive and positively framed language may reduce react-
ance, and, handsfree technology may be acceptable even to
the worst offenders.

Acknowledgments

We thank The Ohio State’s Decision Psychology research colloquium
and three reviewers for comments and suggestions.

Disclosure statement

The authors have no conflicts of interest to disclose.

Funding

This work was supported by grants from The Risk Institute at The Ohio State University, Ohio Department of Transportation, and the National Science Foundation (SES-1558230).

Data availability

Data used in this paper are available at https://osf.io/3ydzx

References

Ajzen I. 1991. The theory of planned behavior. Organ Behav Hum
Decis Process. 50(2):179–211. doi:10.1016/0749-5978(91)90020-T
Bergmark RW, Gliklich E, Guo R, Gliklich RE. 2016. Texting while
driving: the development and validation of the distracted driving
survey and risk score among young adults. Inj Epidemiol. 3(1):7.
doi:10.1186/s40621-016-0073-8
Burstein P. 2003. The impact of public opinion on public policy: a
review and an agenda. Political Res Q. 56(1):29–40. doi:10.1177/
10659129030560103
Caird JK, Simmons SM, Wiley K, Johnston KA, Horrey WJ. 2018.
Does talking on a cell phone, with a passenger, or dialing affect
driving performance? An updated systematic review and meta-anal-
ysis of experimental studies. Hum Factors. 60(1):101–133. doi:10.1177/0018720817748145
Carpenter CJ. 2013. A meta-analysis of the effectiveness of the "But
you are free" compliance-gaining technique. Commun Stud. 64(1):
6–17. doi:10.1080/10509742.2012.727941
Curry AE, Peek-Asa C, Hamann CJ, Mirman JH. 2015. Effectiveness of
parent-focused interventions to increase teen driver safety: a critical
review. J Adol Health. 57(1):S6–S14. doi:10.1016/j.jadohealth.2015.
01.003
Delgado MK, McDonald CC, Winston FK, Halpern SD, Buttenheim AM, Setubal C, Huang Y, Saulsgiver KA, Lee Y-C. 2018. Attitudes on technological, social, and behavioral economic strategies to reduce cellphone use among teens while driving. Traffic Inj Prev. 19(6):569–576. doi:10.1080/15389588.2018.1458100

Delhomme P, Verlhac J-F, Martha C. 2009. Are drivers’ comparative risk judgments about speeding realistic? J Safety Res. 40(5):333–339. doi:10.1016/j.jsr.2009.09.003

Dillard JP, Shen L. 2005. On the nature of reactance and its role in persuasive health communication. Commun Monogr. 72(2):144–168. doi:10.1080/03637750500111815

Dingus TA, Guo F, Lee S, Antin JF, Perez M, Buchanan-King M, Hankey J. 2016. Driver crash risk factors and prevalence evaluation using naturalistic driving data. Proc Natl Acad Sci USA. 113(10):2636–2641. doi:10.1073/pnas.1513271113

Fernandes R, Hatfield J, Soames Job RF. 2010. A systematic investigation of the differential predictors for speeding, drink-driving, driving while fatigued, and not wearing a seat belt, among young drivers. Transp Res Part F Traffic Psychol Behav. 13(3):179–196. doi:10.1016/j.trf.2010.04.007

Gallagher KM, Updegraff JA. 2012. Health message framing effects on attitudes, intentions, and behavior: a meta-analytic review. Ann Behav Med. 43(1):101–116. doi:10.1007/s12160-011-9308-7

Hall MG, Sheeran P, Noar SM, Boynton MH, Ribisl KM, Parada H, Jr Johnson TO, Brewer NT. 2018. Negative affect, message reactance and perceived risk: how do pictorial cigarette pack warnings change quit intentions? Tob Control. 27(e2):e136–e142. doi:10.1136/tobacco-control-2017-053972

Levin IP, Schneider SL, Gaeth GJ. 1998. All frames are not created equal: a typology and critical analysis of framing effects. Organ Behav Hum Decis Process. 76(2):149–188. doi:10.1006/obhd.1998.2804

National Center for Statistics and Analysis. 2019. 2018 fatal motor vehicle crashes: overview. Washington (DC): National Highway Traffic Safety Administration.

Overton TL, Rives TE, Hecht C, Shafi S, Gandhi RR. 2015. Distracted driving: prevalence, problems, and prevention. Int J Inj Contr Saf Promot. 22(3):187–192. doi:10.1080/17457300.2013.879482

Oviedo-Trespalacios O, Williamson A, King M. 2019. User preferences and design recommendations for voluntary smartphone applications to prevent distracted driving. Transp Res Part F Traffic Psychol Behav. 64:47–57. doi:10.1016/j.trf.2019.04.018

Richard CM, Magee K, Bacon-Abdelmoteleb P, Brown JL. 2018. Countermeasures that work: a highway safety countermeasure guide for state highway safety offices. 9th ed. Washington (DC): National Highway Traffic Safety Administration. Report No. Dot Hs 812 478.

Rosenstock IM. 1966. Why people use health services. Milbank Mem Fund Q. 44(3):94–127. doi:10.2307/3348967

Sanbonmatsu DM, Strayer DL, Behrends AA, Ward N, Watson JM. 2016. Why drivers use cell phones and support legislation to restrict this practice. Accid Anal Prev. 92:22–33. doi:10.1016/j.aap.2015.03.010

Schroeder P, Wilbur M, Peña R. 2018. National survey on distracted driving attitudes and behaviors – 2015. Washington (DC): National Highway Traffic Safety Administration. Report No. DOT HS 812 461.

Shavelin BRK, Goodwin KA. 2019. Past behavior and the decision to text while driving among young adults. Transp Res Part F Traffic Psychol Behav. 60:58–67. doi:10.1016/j.trf.2018.09.027

Tapp A, Nancarrow C, Davis A. 2015. Support and compliance with 20mph speed limits in Great Britain. Transp Res Part F Traffic Psychol Behav. 31:36–53. doi:10.1016/j.trf.2015.03.002

Weller JA, Shackleford C, Dieckmann N, Slovic P. 2013. Possession attachment predicts cell phone use while driving. Health Psychol. 32(4):379–387. doi:10.1037/a0029265

Windschitl PD, Wells GL. 1996. Measuring psychological uncertainty: verbal versus numeric methods. J Exp Psychol Appl. 2(4):343–364. doi:10.1037/1076-898X.2.4.343