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A randomized pilot trial of a mobile phone–based brief intervention with personalized feedback and interactive text messaging to reduce driving after cannabis use and riding with a cannabis impaired driver

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Abstract

Introduction: Driving after cannabis use (DACU) and riding with a cannabis-impaired driver (RWCD) are national public health concerns. Though driving impairments and increased crash risk make DACU and RWCD two of the riskiest cannabis-related behaviors, many continue to drive after use and ride with others who are under the influence and do not view DACU or RWCD as dangerous. The current study examined the efficacy of an accessible, low-cost, mobile phone–based brief intervention aimed at reducing DACU and RWCD among college cannabis users in the context of a randomized three-group pilot trial.

Method: Participants were 97 college cannabis users (67.4 % women; average age = 21.34; 80.4 % Caucasian) who endorsed DACU at least three times in the past three months. After completing baseline measures, the study randomly assigned participants to one of three conditions: a) a substance impaired–driving personalized feedback plus MI-style interactive text messaging intervention (PF + MIT); b) a substance impaired–driving personalized feedback only intervention (PF); and c) a substance information control condition (IC). All conditions completed outcome measures three months postintervention.

Results: Generalized linear mixed models (GLMM) analyses indicated that after controlling for sex, cannabis users in the PF + MIT condition significantly reduced DACU and RWCD over time compared to those in the IC condition.

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CRediT authorship contribution statement

Jenni Teeters: Funding acquisition, Conceptualization, Methodology, Formal analysis, Writing Original Draft, Revisions. Nicole Armstrong: Data analyses and Table 2.

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Declaration of competing interest

Conclusions: These findings provide preliminary support for the short-term efficacy of a mobile phone–based intervention in decreasing DACU and RWCD among college cannabis users. Future research should determine whether these reductions in driving behaviors persist past three months.

Keywords

Cannabis; Driving; Text-messaging; Intervention; College

1. Introduction

Substance-impaired driving is a significant public health concern. Years of epidemiological and experimental research have demonstrated that cannabis use impairs driving ability (e.g., slower reaction time, delayed responses to road obstacles, impaired road tracking control) and cognitive functioning (e.g., memory, attention, decision making, impulse control) and increases risk for traffic accidents (Asbridge et al., 2012; Hartman & Huestis, 2013; Hostiuc et al., 2018; Kelly et al., 2004; Li et al., 2012). Although rates of driving after drinking have decreased over time (Hingson et al., 2017), rates of driving after cannabis use (DACU) continue to rise (Schulenberg et al., 2020). In 2018, 12 million US adults (4.7 %) reported driving after cannabis use (12.4 % for adults ages 21-25). Cannabis is the most prevalent illicit drug detected among drug-impaired drivers, and the most frequently used illicit drug among emerging adults (Brady & Li, 2013; Johnstonet al, n.d.). Rates of cannabis involved traffic fatalities have increased in states with recreational cannabis compared to their neighboring jurisdictions (Lane & Hall, 2019) and cannabis users who report DACU are significantly more likely to report being involved in a collision in the past year (Mann et al., 2007). In addition, data from recent roadside surveys suggest that positive tests for delta-tetrahydrocannabinol (THC) have increased in recent years and that drivers with a child in the car were much more likely to test positive for cannabis than for alcohol (14.1 % vs. 0.4 %; Berning et al., 2015; Romano et al., 2019). Given the increased prevalence of lifetime and daily cannabis use among emerging adults, DACU is becoming an increasingly urgent concern (Kerr et al., 2018; Melchior et al., 2019; Parnes et al., 2018).

Another risky impaired driving behavior that has received considerably less attention is riding with a cannabis-impaired driver (RWCD). Recent research demonstrates that many adolescents and young adults report riding with an impaired driver, with rates ranging from 20 % to 33 % in the past year depending on the sample (Carpino et al., 2020; Li et al., 2014, 2018). Attending a 4-year college and simultaneous use of alcohol and cannabis have been shown to increase the likelihood of riding with an impaired driver (Li et al., 2018; Patrick et al., 2021). Riding with an impaired driver has been linked to greater risk of problematic alcohol and cannabis use (Osilla et al., 2019) and driving under the influence of alcohol and cannabis (Li et al., 2018). Previous research has linked lower perceived risk of regular cannabis use to greater risk of DACU and RWCD (Carpino et al., 2020). Due to the high rates and potentially fatal consequences associated with RWCD, prevention and intervention efforts targeting RWCD are imperative.

Brief interventions (BIs) attempt to identify and correct faulty normative beliefs and highlight consequences of substance use (such as driving after substance use) to increase

motivation to change a problematic behavior. BIs typically consist of one or two individual therapeutic meetings (approximately 50 min per session) delivered in motivational interviewing (MI) style and include personalized feedback (Carey et al., 2007; Miller & Rollnick, 2013). A series of questionnaires completed by the participant prior to their BI session make up the information provided in the personalized feedback document. Although specific feedback components may differ, studies typically include a personalized substance use profile, information on social norms, prior substance-related consequences experienced by the participant (including driving after substance use if endorsed), practical costs (e.g., money spent on substances), and information on strategies to limit substance-related risk (Miller et al., 2013). Recent meta-analyses indicate that brief alcohol interventions generally succeed in reducing alcohol use (frequency, quantity, level of intoxication) and a variety of alcohol-related problems, although effect sizes are typically small (Tanner-Smith & Lipsey, 2015).

Notably, personalized feedback interventions delivered to emerging adult cannabis users have demonstrated limited efficacy for decreasing cannabis use and problems (Halladay et al., 2019). A recent systematic review and meta-analysis by Halladay and colleagues (Halladay et al., 2019) on BIs for cannabis use in emerging adults examined evidence from 26 studies including 6318 participants (ages 16–29) and found that existing cannabis-related BIs resulted in small reductions in symptoms of cannabis use disorder and increased likelihood of cannabis abstinence but did not result in significant reductions in frequency of cannabis use and related problems. These findings parallel results from other meta-analyses conducted by Imtiaz et al. (2020) and Tanner-Smith et al. (2021) that showed BIs for cannabis use delivered in health care settings did not result in reductions in cannabis use. Though evidence for improving cannabis-related outcomes via BIs has been mixed, given the cost effectiveness of BIs and increased likelihood for engagement among emerging adults compared with longer-term psychosocial treatments, BIs remain important within a stepped-care approach to substance use and warrant further evaluation and development (Halladay et al., 2019).

Research suggests that personalized feedback delivered without a one-on-one, counselordelivered intervention may effectively reduce alcohol use and problems at short-term follow-ups (up to 4 months), but direct comparisons of feedback only interventions vs. face-to-face interventions favor clinician contact and suggest that effects of interventions delivered without clinician contact tend to be smaller and dissipate at longer term follow-ups (Cadigan et al., 2015; Carey et al., 2012). In the only previously published study to examine the impact of a BI on DACU (as a secondary outcome), Walton et al. (2013) conducted a head-to-head test of a computer delivered vs. a therapist delivered cannabis BI and found a significant condition difference for driving under the influence (DUI) of cannabis, such that only participants who received the therapist delivered BI significantly reduced the frequency of cannabis related DUI (Walton et al., 2013).

Previous research has shown that in-person, counselor delivered BIs can successfully reduce alcohol impaired driving among DUI offenders, emergency department patients, and college students (Brown et al., 2010; D'Amico et al., 2018; Mun et al., 2021; Ouimet et al., 2013; Schermer et al., 2006; Teeters et al., 2015). In the past few years, a number of BIs using

text-messaging to target substance use and problems have been developed and evaluated. Research by Heron et al. (2019) showed that among 1371 college students, 99.5 % owned smartphones, 94.6 % had unlimited texting, and 96.8 % reported texting at least once per day. Delivering BIs through text message allows for low-cost delivery to a large number of people and allows researchers to personalize information and interact with participants (Hall et al., 2015). A meta-analysis conducted by Mason et al. (2015) concluded that text-messaging interventions show a positive effect on reducing substance use behaviors (overall pooled effect size for 14 RCTs Cohen's d=0.25; Mason et al., 2015). Research indicates that emerging adults rate text-messaging interventions as highly acceptable and prefer texting to emails and telephone calls (Common Sense, 2018; Mason et al., 2018).

Several recent studies have demonstrated greater effectiveness of interventions that include personal contact vs. those that are fully automated (Drislane et al., 2019; Riper et al., 2018). Teeters et al. (2018) conducted a pilot trial of a mobile phone–based intervention including personalized feedback and interactive text messages aimed at reducing alcohol-impaired driving among college students and found that students who received the mobile phonebased BI reported significantly greater reductions in likelihood of driving after drinking (OR = 0.016) and the number of drinks consumed prior to driving than students in the information condition at three-month follow-up (Teeters et al., 2018). To our knowledge, this was the first study to demonstrate that a mobile phone-based BI specifically targeting driving after drinking can reduce alcohol-impaired driving in this population. Additionally, Teeters et al. (2021) investigated whether the brief mobile-based intervention would lead to changes in DACU related cognitions and found that the personalized feedback and interactive text-messaging intervention were associated with larger increases over time in the perceived dangerousness of DACU compared to the control condition (p = .01; Cohen's d = 0.79; Teeters et al., 2021). Although the results of Teeters et al. (2021) are promising, assuming that changes in explicit cognitions (dangerousness of DACU) will lead to behavior change is speculative (decreases in DACU over time).

To directly test this important question, the current study utilizes the same intervention model in an attempt to reduce DACU. The overall goal of the current study is to examine the efficacy of an accessible, low-cost, mobile phone–based BI aimed at reducing DACU among college cannabis users. Given the link between DACU and RWCD (Li et al., 2018), the study added a secondary outcome of RWCD post-hoc and examined it to determine if the intervention also resulted in reductions in this risky behavior. In the current study, the efficacy of an intervention with personalized feedback plus MI-style interactive textmessaging (PF + MIT) was compared to a) personalized feedback (PF) only and b) a substance informational control (IC) condition in the context of a randomized 3-group (PF + MIT vs. PF vs. IC) trial. The PF condition was included to parse out the unique contribution of the interactive text-messaging above and beyond the personalized feedback components.

2. Method

2.1. Participants

Participants were 97 undergraduate students from a public university in the mid-southern United States. The university resides in a small city with a population of approximately

67,600 individuals. To be eligible, students had to be at least 18 years or older, have access to a motor vehicle and a valid driver's license, and report driving after cannabis use at least three times in the past three months. Additionally, participants had to have access to a smart phone, willingness to read intervention material and exchange a brief series of text messages via a secure mobile app with encryption technology postintervention with the study administrator. The study excluded individuals from the study if they were in treatment for substance use. Participants were 67.4 % women, 30.5 % men, and 80.4 % Caucasian, 7 % African American, 2 % Asian, 1 % Hispanic or Latino, 3 % other, and 8 % multiple selected. The average age of the participants was 21.34 years (SD = 4.24). A quarter of participants in the sample endorsed driving after combined use of alcohol and cannabis in the past 3 months, and 85.3 % of participants endorsed at least 1 heavy episodic drinking episode in the past month (4 or more drinks on one occasion for females and 5 or more drinks on one occasion for males). Rates of past month recreational drug use in the sample were as follows: cocaine (20.6 %), hallucinogens (30.9 %), heroin (1 %), methamphetamine (2.1 %), prescription pain killers (7.2 %), stimulants (19.6 %), and sedatives (13.4 %).

2.2. Measures

The study collected all measures at Time 1 (pre-intervention) and again at Time 2 (3 months postintervention).

2.2.1. Demographics—Participants completed a brief questionnaire that assessed participant sex, age, ethnicity, and past and present academic status.

2.2.2. Cannabis use—The study used a modified, brief computer-delivered Timeline Follow-Back (TLFB; Sobell et al., 1996) to assess cannabis use during the past 7 days prior to the baseline appointment. Additionally, participants were asked to report the number of days they used cannabis in the past month.

2.2.3. Driving after cannabis use—The study assessed driving after cannabis use via the following question, "In the past 3 months, how many times have you driven after using marijuana?" The study adapted this question from prior studies that asked students how many times they have driven after using cannabis in the past 3 months (Arterberry et al., 2017).

2.2.4. Riding with a driver under the influence of cannabis—Riding with a driver under the influence of cannabis was assessed via the question, "How many times in the past 3 months have you been the passenger in a vehicle with a driver who has been using marijuana?"

2.3. Procedures

The university Institutional Review Board approved all procedures and participants were assured that all data would be confidential. The study recruited participants through a mass university-wide email, the university subject pool, and flyers posted on campus. Following an eligibility screener survey, trained lab personnel contacted eligible participants by phone and invited them to participate in the clinical trial (clinicaltrials.gov

NCT03496129). Eligible students who wished to participate were then sent a 30-minute baseline questionnaire via text-message to be completed remotely on their mobile phone via a secure web server. After completing the battery of online measurements, the study randomly assigned participants via a random number generator to one of three conditions (stratified by gender Fig. 1), 1) a substance impaired–driving personalized feedback plus MI-style interactive text messaging intervention (PF + MIT); 2) a substance impaired–driving personalized feedback only intervention (PF); and 3) a substance information control condition (IC). All conditions included a 3-month follow-up. The study gave participants a \$20 Amazon gift card or 3 subject pool credits for completion of the baseline questionnaire and intervention, and a \$15 Amazon gift card or 2 subject pool credits for the follow-up questionnaire. All data included in this manuscript come from the baseline assessment and 3-month follow-up for participants endorsing DACU (collected between August 2018 and December 2019). Data related to a 6-month follow-up were collected but due to the impact of the Covid-19 pandemic, the study team was unable to collect one fourth of 6-month follow-up.

2.3.1. Substance impaired-driving personalized feedback only intervention

(PF)—Following the baseline assessment, the study sent participants in the PF condition a link via text message to a secure website containing personalized feedback. The feedback document included a personalized cannabis use profile and DACU profile and information on social norms related to cannabis use and DACU. The document also contained self-reported cannabis impairment and physical effects of cannabis use, costs associated with a DUI citation in Kentucky, and information on combined cannabis and alcohol impaired—driving risk (if endorsed). Participants were instructed to view the personalized feedback document and respond to a number of questions (determined based on participants' responses to the questionnaires) embedded in the document as a comprehension and fidelity check. For example, the first question asks participants to choose the percentage of students who reported NO substance impaired—driving in the past 3-months (based on a figure provided in the personalized feedback).

2.3.2. Substance impaired-driving personalized feedback plus interactive text messaging intervention (PF + MIT)—Following the baseline assessment, the study sent participants in the PF + MIT condition a link via text message to a secure website containing personalized feedback (described above). In addition to viewing the feedback document and responding to the embedded attention checks, the study asked participants to reply via a text message to the study administrator to confirm receipt and processing of the feedback document. Next, a trained interventionist sent the participant text messages containing the following open-ended questions: 1) Of the information you just viewed, what was most interesting? 2) How would receiving a DUI impact your future career goals?
3) What is your plan for driving after substance use in the future? and 4) What specific goals would you be willing to set (if any) related to driving after substance use? Based on participants' responses to these open-ended questions, the interventionist sent follow-up text messages to provide appropriate reflection/encouragement in motivational interviewing (MI) style. All interventionists were trained in MI, and a clinical psychologist with expertise in MI supervised the text messaging interactions. The intervention was a single session, and

the average number of text messages exchanged between the interventionist and participants during the interactive texting portion of the intervention was 18 (range = 10-31). The average time to complete the intervention was 57 min.

2.3.3. Substance information condition (IC)—Participants randomized to the information condition received standard information about alcohol, cannabis, and substance impaired–driving via a link to a website delivered through text message. The informational document was roughly equivalent in length to the personalized feedback documents, contained the same number of attention checks, and provided detailed information about how alcohol, drugs, and combining alcohol and other drugs affect the brain and nervous system, memory, and driving performance. This intervention was designed to be similar to substance education programs commonly found on college campuses and contained no personalized information.

2.4. Data analysis plan

The study team conducted analyses using SPSS version 27.0 and R version 4.1.0. To minimize the impact of outliers, values >3.29 SDs above the mean on a given variable were Winsorized to one unit greater than the greatest nonoutlier value (Tabachnick & Fidell, 2013). Notably, all data reported were collected prior to the Covid-19 pandemic, which drastically impacted driving rates (Gupta et al., 2021).

The research team collected baseline descriptive characteristics of the overall sample, including demographic information (sex, age, ethnicity) as well as the means and standard deviations for the primary outcome variables (driving after cannabis use and riding with a cannabis impaired driver). Additionally, the team performed *t*-tests and chi square analyses to determine whether the conditions were significantly different at baseline on any demographic or cannabis-related variables (Table 1).

The primary study analyses examined whether a statistically significant difference existed between intervention conditions on changes in driving after cannabis use or riding with a cannabis-impaired driver. The team conducted repeated measures mixed modeling analyses to examine study hypotheses: 1) participants in the PF + MIT and PF conditions will report greater reductions in DACU over time compared to participants in the IC condition, 2) participants in the PF + MIT condition will report greater reductions in DACU than participants in the PF condition, 3) participants in the PF + MIT and PF conditions will report greater reductions in RWCD over time compared to participants in the IC condition, and 4) participants in the PF + MIT condition will report greater reductions in RWCD than participants in the PF condition. Mixed modeling examines data similarly to repeated measures ANOVA; however, mixed modeling provides increased flexibility in handling missing data by utilizing all available data for each participant and provides ease of adaptation for multiple research designs (Hox, 2013).

Generalized linear mixed models (GLMM) represent an extension of linear mixed models to non-normal data. GLMM with a negative binomial distribution, which allows for overdispersion in count outcomes, with a log link function were utilized for outcomes of non-normally distributed count data (i.e., total number of times driving after cannabis use

and riding with a cannabis-impaired driver). The study used lme4 package in R to run these models. We found DACU and RWCD to be over dispersed (i.e., variance exceeds mean). For each model tested, DACU or RWCD served as the dependent variable. Given previous research showing sex differences in rates of cannabis use and evidence of sex differences in response to brief substance use interventions (Reinhardt et al., 2008), the study included sex a priori as a covariate in all models. The study estimated models with random intercepts and time as a fixed effect. Models included the dummy-coded variables for PF + MIT vs. IC as well as PF vs. IC as well as the two-way interactions between these dummy-coded variables and time (coded as 0 = Baseline and 1 = Follow-up) since study initiation. The study tested contrasts to compare baseline PF + MIT vs. PF as well as the two-way interactions of PF + MIT and PF with time post hoc by *t*-tests. The research team computed Cohen's *d* effect sizes and interpreted them using the conventional metrics of d = 0.2, 0.5 and 0.8 indicating small, medium, and large effects (Cohen, 1992).

3. Results

3.1. Baseline and 3-month follow-up characteristics

Overall, participants reported driving after cannabis use an average of 25.2 times (SD = 24.62) in the past 3 months at baseline and 19.92 times (SD = 24.50) in the past 3 months at the 3-month follow-up. Participants reported riding with a driver who was under the influence of cannabis 14.49 times (SD = 19.41) at baseline and 9.52 times (SD = 14.12) in the past 3 months at 3-month follow-up. Participants reported using cannabis on an average of 20 days (SD = 9.55) in the past month at baseline and on an average of 17.8 days (SD = 10.44) at 3-month follow-up. Interestingly, 48 participants (49.5 %) reported using a ride-share service (i.e., Uber, Lyft) in the past 3 months after drinking alcohol whereas only 3 participants (3 %) reported using a ride-share service after using cannabis. The study found no significant baseline differences on demographic or outcome variables (see Table 1). Eight participants did not complete the 3-month follow-up (93.6 % overall follow-up rate; 2 from the PF condition, 4 from the IC condition, and 2 from the PF + MIT condition).

3.2. Analysis of study outcomes

We present results for the mixed models analyses in Table 2.

3.2.1. Driving after cannabis use—The study used generalized linear mixed models (GLMM) with a negative binomial distribution to determine whether participants in the PF + MIT condition displayed significantly greater reductions in DACU over time compared to participants in the IC and PF conditions. In a model with dummy-coded variables for PF + MIT and PF conditions (controlling for sex), the PF + MIT intervention was associated with significantly greater reductions in DACU over time compared to the IC condition (p < .05; Cohen's d = 0.31). The study found no difference in slopes between the PF and IC conditions. When we examined post-hoc analyses comparing PF + MIT and PF conditions to one another, we did not find differences between these two interventions. PF + MIT participants (N = 38) significantly decreased their number of times DACU over time (Cohen's d = 0.42), while participants in the PF condition (N = 28) did not change their

number of times DACU (Cohen's d = 0.00), and participants in the IC condition (N = 31) displayed slight decreases in DACU over time (Cohen's d = 0.13; see Fig. 2).

3.2.2. Riding with a driver under the influence of cannabis—The study used generalized linear mixed models (GLMM) with a negative binomial distribution to determine whether participants in the PF + MIT condition displayed significantly greater reductions in RWCD over time compared to participants in the IC and PF conditions. In a model with dummy-coded variables for PF + MIT and PF conditions (controlling for sex), the PF + MIT intervention was associated with significantly greater reductions in RWCD over time compared to the IC condition (p < .001; Cohen's d = 0.14). The study found no difference in slopes between the PF and IC conditions. When we examined post-hoc analyses comparing PF + MIT and PF conditions to one another, we did not find differences between these two. PFT participants (N = 38) significantly decreased their number of times riding with a driver who was under the influence of cannabis (Cohen's d = 0.32), as did participants in the PF condition (Cohen's d = 0.35). Participants in the IC condition (N = 31) displayed no differences in riding with a driver who was under the influence of cannabis (Cohen's d = 0.04) (Fig. 3).

4. Discussion

Driving after cannabis use (DACU) and riding with a cannabis-impaired driver (RWCD) among emerging adults are significant public health concerns and represent two of the riskiest cannabis-related behaviors in terms of potential for fatal consequences. The current study evaluated a brief, mobile phone–based personalized feedback and MI-style interactive text messaging intervention to reduce DACU and RWCD among college cannabis users. The results provide initial support for the efficacy of this intervention. The article discusses specific findings below in conjunction with study limitations, implications, and future directions.

Consistent with previous research examining BIs to reduce alcohol-impaired driving among college students, DUI offenders, and emergency room patients (Brown et al., 2010; D'Amico et al., 2018; Mun et al., 2021; Ouimet et al., 2013; Schermer et al., 2006; Teeters et al., 2015), the current study found that a BI including personalized feedback led to significantly greater reductions in impaired driving compared to a control condition. These findings align with recently published findings by Mun and colleagues (Mun et al., 2021) that examined whether BIs reduce driving after drinking among college students. They compared: a) group motivational interviewing, b) BIs with stand-alone personalized feedback, and c) BIs including MI with personalized feedback and found that BIs including MI and personalized feedback outperformed the other two interventions in terms of reducing driving after 4+/5+ drinks. The findings of the current study extend these findings to DACU and RWCD, increasingly common risk behaviors reported by emerging adults. These results also add promising findings to the literature on cannabis-related BIs. Though meta-analyses and reviews of BIs targeting frequency of cannabis use have failed to show sustained reductions in frequency of cannabis use (Halladay et al., 2019; Imtiaz et al., 2020; Tanner-Smith et al., 2021), the results reported here provide preliminary evidence that a BI targeting a specific cannabis-related risk behavior, in this case driving after cannabis

use, can successfully reduce this high-risk behavior without reducing overall cannabis-use frequency. Targeting specific risky behaviors associated with cannabis use, rather than focusing solely on frequency of use, is important from a harm reduction perspective and should be considered in future work aiming to reduce harm associated with cannabis use.

The findings of the current study also add to the literature on mobile-based interventions for substance impaired driving. Utilizing the same intervention approach with drinking drivers, Teeters et al. (2018) conducted a pilot trial with 84 college student drinkers (67.1 % women; average age = 23; 52.4 % Caucasian) who endorsed driving after drinking two or more drinks at least twice in the past three months. Generalized linear mixed modeling (GLMM) analyses revealed that students who received the mobile phone–based BI decreased their alcohol-impaired driving behaviors. The current study replicates and extends these findings in a sample of cannabis users endorsing recent DACU. Furthermore, these results show that the intervention not only resulted in changes in cognitions related to perceived dangerousness of DACU as found by Teeters et al. (2021), but also resulted in changes in cannabis-impaired driving behaviors.

Interestingly, the study found that the personalized feedback (PF) only condition did not result in significantly greater reductions in DACU than the information control (IC) condition. Though not significantly different from one another, the mean number of times DACU in the control condition decreased slightly over time while the mean number of times DACU in the PF condition remained almost identical from baseline to 3-month follow-up. While surprising, this finding may have been due to the nature of the control condition used in this study. Rather than using an assessment only or waitlist control, the current study included an informational control that was visually similar to the personalized feedback document (same number of graphics and pages) and included similar content (information on risks associated with substance use and substance-impaired driving). The only difference between the personalized feedback and the information conditions were that the information document contained only generic information and did not include any personalized content based on participants' responses to the baseline questionnaire. The study team chose this control condition in an attempt to match information typically provided to students through general substance education programs, such as AlcoholEdu (an online program required by many college campuses prior to starting classes). In reality, the control condition likely provided much more information on the impact of cannabis use on driving abilities than is typical in standardized programs required by college campuses, which may have accounted for our finding that both the PF and IC conditions led to decreases in DACU over time.

Notably, effect size reductions in DACU were greater over time for participants in the PF + MIT condition compared to participants in the PF and IC conditions. Previous research directly comparing feedback only interventions vs. face-to-face interventions favor clinician contact and suggest that effects of interventions delivered without clinician contact tend to be smaller and dissipate at longer term follow-ups (Cadigan et al., 2015; Carey et al., 2012). Given these findings, we expected that the PF + MIT intervention would lead to significantly greater decreases in DACU compared to the PF intervention due to the MI text-messages. The current findings suggest that the extra resources associated with training an interventionist to deliver the MI text-messaging portion of the intervention may

have been justified given that participants in the PF + MIT condition showed the greatest decreases over time in DACU. However, this conclusion remains speculative as the PF + MIT condition was not compared to an automated text-messaging condition, making it impossible to determine if employing an interventionist was crucial to these findings. Future research comparing personalized feedback and clinician delivered text-messaging to personalized feedback with automated text-messaging is especially important given that the interventionist component may reduce scalability of intervention dissemination.

4.1. Limitations

The current study has several limitations that should be considered when interpreting these findings. The sample size was lower than anticipated due to the Covid-19 pandemic. A planned second wave of data collection that would have resulted in a sample of 150 participants (50 per condition) was not able to be collected due to the pandemic coinciding with the termination of the grant funding period. The team paused data collection at the outbreak of the pandemic due to the drastic reductions in driving rates due to lockdown measures (Gupta et al., 2021). However, that significant effects were detected between the PF + MIT intervention vs. the information control condition is extremely promising given the lower-than-anticipated power to detect small effects. Future research replicating this procedure in a larger sample of emerging adults would lend increased confidence to the current findings. Furthermore, the study collected all cannabis use data via retrospective self-reports and measures did not account for how much cannabis was used before driving, timeframe of use, type of product, or potency of product used. Accurate assessments of cannabis use are common problems within cannabis research (Cuttler & Spradlin, 2017). Future research should include additional details related to cannabis use to gain a more nuanced assessment of intoxication and impairment levels prior to driving. While selfreport measures can be subject to biases, research comparing self-reported cannabis use to biological measures (hair and urine sample) showed that self-reported frequency of use was the best predictor of clinician rated cannabis dependence (Curran et al., 2019). Furthermore, the study examined intervention effects only from baseline to 3 months postintervention, making it impossible to determine if effects would have persisted following this 3-month period. Future research should include longer-term follow-ups as previous research has shown that effects of BIs tend to shrink over time (Foxcroft et al., 2016). The current research is also limited in terms of generalizability given that the majority of the sample were White (80.1 %), female (67.4 %) college students. Future research should include more diverse samples to determine the efficacy of this intervention. Despite these limitations, the study has potential public health implications as it shows promising outcomes for changes in DACU and RWCD using a highly accessible, brief mobile phone-based intervention with personalized feedback and interactive text messaging.

4.2. Implications

Overall, the current study provides preliminary evidence that a mobile delivered BI with personalized feedback and MI-style interactive text-messaging results in significantly greater decreases in DACU and RWCD compared to an informational control. This is the first study to recruit based on recent DACU and specifically target DACU and RWCD. In addition to replicating the intervention in a larger sample and including longer-term follow-ups,

future research should examine the impact of the intervention on driving after the combined use of alcohol and cannabis, an extremely risky behavior that is becoming more prevalent among emerging adults. Future research should also include noncollege emerging adults given recent increases in daily cannabis use among this population. Additionally, recent research on event-level predictors of alcohol-impaired driving using ecological momentary assessment suggests that momentary subjective judgments (perceptions of intoxication levels and dangerousness of driving after drinking) are the strongest predictors of intentions to drive after drinking (Motschman et al., 2020). Future work should determine if these findings replicate with intentions to drive after cannabis use. If so, an optimal intervention to reduce DACU and RWCD may combine a BI approach with just-in-time messages designed to increase perceptions of dangerousness and/or provide information on intoxication level in-the-moment in naturalistic settings.

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Fig. 1.

Flowchart illustrating recruitment, intervention and follow-up assessment for participants endorsing driving after cannabis use. All participation occurred remotely via text messages and email/web links.

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Fig. 2.

Number of times driving after cannabis use (+/-1 SEM) over time by condition (personalized feedback + MI text messages, feedback only, information only). Note: SEM = standard error of mean.

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Fig. 3.

Number of times riding with a driver under the influence of cannabis (+/-1 *SEM*) over time by condition (personalized feedback + MI text messages, feedback only, information only). Note: SEM = standard error of mean.

Table 1

Descriptive statistics for outcome variables and covariates: baseline and 3-month follow-up.

	Total sample (<i>N</i> = 97)	$\mathbf{PF} + \mathbf{MIT}$ $(n = 38)$	PF (<i>n</i> = 28)	Information $(n = 31)$	Statisti $\chi^2 \Phi$	ical test
Gender						
Male	n = 29 (30.5 %)	n = 10 (34.5 %)	n = 10 (34.5 %)	n = 9 (31 %)		
Female	$n = 64 \ (67.4 \ \%)$	n = 25 (39.1 %)	n = 18 (28.1 %)	n = 21 (13.4 %)		
Statistical test					0.39	0.81
Ethnicity White	$n = 78 \ (80.4 \ \%)$	n = 27 (34.6 %)	n = 25 (32.1 %)	n = 26 (33.3 %)		
Non-White	n = 19 (19.6 %)	n = 11 (57.9 %)	<i>n</i> = 3 (15.8 %)	n = 5 (26.3 %)		
Statistical test					3.75	0.19
	M (SD)	M (SD)	M (SD)	M (SD)	Statistical test	
					F	р
Age	21.34 (4.24)	22.24 (5.37)	21.21 (4.09)	20.35 (4.26)	1.71	0.19
Driving after cannabis use Baseline	25.16 (24.62)	26.50 (26.55)	22.43 (21.39)	26.00 (25.46)	0.243	0.79
3-Month	19.92 (24.47)	15.82 (19.81)	22.36 (29.49)	22.74 (24.78)	0.877	0.42
Riding with cannabis impaired driver Baseline	14.49 (19.41)	17.55 (22.51)	14.18 (19.32)	12.45 (20.21)	0.399	0.80
3-Month	9.52 (14.12)	9.16 (16.44)	8.07 (9.77)	11.33 (14.62)	0.383	0.82
Driving after combined use of alcohol and cannabis Baseline	0.98 (2.60)	0.84 (2.59)	0.89 (1.66)	1.23 (3.31)	0.20	0.81
3-Month	0.51 (1.42)	0.18 (0.69)	0.57 (1.64)	0.84 (1.79)	1.18	0.15
Past month cannabis use days Baseline	20.44 (9.58)	20.92 (8.67)	20.89 (10.19)	19.43 (10.27)	0.238	0.79
3-Month	17.77 (10.44)	15.72 (10.60)	18.68 (10.18)	19.32 (10.42)	1.15	0.32

Note: 4 participants did not identify as male or female.

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Table 2

Fixed effects from generalized linear mixed models with sex as a covariate.

Factor	Fixed Effects	SE	Z	95 % CI
DACU: PF + MIT and PF vs. IC		~		
Intercept	3.06	0.26	11.73 ***	(2.551–3.575)
Condition - PF + MIT vs. IC	-0.13	0.28	-0.45 **	(-0.679-0.425)
Condition - PF vs. IC	-0.20	0.30	-0.67	(-0.783-0.385)
Sex $(1 = \text{women}, 0 = \text{male})$	-0.10	0.22	-0.45	(-0.539-0.339)
Time (0 = baseline, 1 = follow-up)	-0.23	0.20	-1.12	(-0.621-0.169)
Condition - PF + MIT vs. IC \times Time	-0.59	0.28	-2.09*	(-1.133 to -0.037)
Condition - PF vs. IC \times Time	-0.07	0.29	-0.25	(-0.647-0.502)
RWCD: PF + MIT and PF vs. IC				
Intercept	1.93	0.32	6.03 ***	(1.306–2.564)
Condition - PF + MIT vs. IC	0.49	0.34	1.44	(-0.177-1.161)
Condition - PF vs. IC	0.16	0.36	0.45	(-0.549-0.875)
Time (0 = baseline, 1 = follow-up)	-0.03	0.21	-0.13	(-0.449-0.391)
Sex $(1 = \text{women}, 0 = \text{male})$	-0.06	0.28	-0.20	(-0.611-0.498)
Condition - PF + MIT vs. IC \times Time	-1.15	0.30	-3.88 ***	(-1.725 to -0.568)
Condition - PF vs. IC \times Time	-0.58	0.31	-1.88	(-1.194-0.025)

Note: DACU = Driving after Cannabis use, RWCD = Riding with a Cannabis-Impaired Driver, PF + MIT = Personalized Feedback + MI style text messages, PF = Personalized Feedback only, IC = Information Control, CI = Confidence Interval. Sex was coded: 1 = women; 0 = men. Time was coded: 0 = baseline 1 = follow-up.

*

** p<.01.

*** p<.001.

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