DISSERTATION

YOU CAN FEEL GOOD: POSITIVE OUTCOMES OF MARIJUANA USE

Submitted by

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ABSTRACT

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To date, limited marijuana research has focused on identifying reinforcing outcomes related to use, often perceived as positive outcomes. Operant conditioning and social learning theories suggest that the reinforcing aspects of substance use are a primary contributor to maintained use, and in turn, risk of dependence. Individuals who use marijuana report expecting positive outcomes which motivates use; however, the occurrence of such positive outcomes are rarely examined. Moreover, research has yet to develop a reliable, validated measure of positive marijuana-related outcomes. The present study sought to develop and psychometrically evaluate such a measure. I hypothesized that: 1) positive outcomes would be positively associated with marijuana use, positive expectancies, and negative outcomes, 2-3) positive outcomes would be unrelated to alcohol use and positive alcohol outcomes, and 4) positive outcomes would account for unique variance in recent use, controlling for expectancies and negative outcomes. Scale items were developed using inductive and deductive methods. College students ($N = 883$) and community adults ($N = 214$) completed a survey measuring marijuana use frequency, positive outcomes, expectancies, and negative consequences. Exploratory and confirmatory factor analysis (CFA) tested scale dimensionality and structure in the college sample and community sample. The final factor structure achieved excellent model fit (CFI = .96-.97, RMSEA = .03-.05) and internal consistency (ω = .84-.90). Four factors emerged from the data: Social Enhancement, Mood Enhancement and Relaxation, Perceptual Enhancement, and Sexual Enhancement. Invariance testing supported configural invariance between the two samples.

Study hypotheses supporting scale validity were largely upheld. Positive outcomes were positively associated with recent use, controlling for expectancies and negative outcomes. Positive outcomes were also either unassociated or negatively associated with alcohol use, and unassociated or weakly associated with alcohol positive outcomes. Positive outcomes were also differentiated from positive expectancies and more influential in predicting typical use frequency. Findings implicate that positive outcomes are an important factor in explaining recent marijuana use, necessitating the need for future longitudinal use to understand their role in maintained use and dependence. Additionally, positive outcomes can be a target for clinical interventions by informing replacement behaviors or enhancing motivational interviewing techniques.

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INTRODUCTION

Understanding negative marijuana-use-related outcomes and their antecedents has been a central focus of marijuana research (e.g., Simons et al., 2012; Pearson, 2019). Rightfully so, as marijuana use is associated with several physical and mental health risks that may pose harm (e.g., impaired memory and judgement; Volkow et al., 2014). Learning theories based on operant conditioning posit that individuals' behaviors are shaped by past experiences and reinforcement (Reynolds, 1975). Extended to individuals who use marijuana, those who experience overly negative outcomes from use should learn to reduce or abstain from use to mitigate these outcomes. Marijuana research has identified a multitude of negative outcomes that may result from use (Simons et al., 2012; Volkow et al., 2014). Individuals who use are often aware of and even expect these negative outcomes to occur (e.g., impaired concentration; Aarons et al., 2001; Simons et al., 2012). This behavior is inconsistent with operant conditioning, as individuals who experience negative outcomes are unlikely to repeatedly engage in the same behavior. Therefore, negative outcome research may minimize the aspects of use that explain why individuals continue using, even in the presence of negative consequences of use.

Several potentially reinforcing aspects of marijuana use have been identified, such as euphoria, relaxation, and reduction of negative affect (Metrik et al., 2011; Osborne & Fogel, 2008). Several of these reinforcing facets are experienced as positive outcomes of use, which may serve as one foundation for maintained use. However, research has yet to develop an adequate measure of these positive outcomes of use. Learning theories, expectancies, dependence, marijuana-related outcomes (i.e., objective and subjective responses), and scale development theories may inform how to best measure positive outcomes of use. Measurement of positive outcomes can then be used to inform how these outcomes relate to other important marijuana-related outcomes (e.g., continued use).

Learning Through Conditioning

To understand how marijuana outcomes occur, and in turn, how to measure them, it is important to understand how individuals come to associate specific outcomes with marijuana use. Conditioning, or pairing of stimuli and responses (Pavlov, 1927) is one theory that helps explain initiation, maintenance of use, development of expected outcomes, and experienced outcomes from use. Initially, unconditioned stimuli and responses become associated through natural experiences (e.g., smelling food and becoming hungry). Through classical conditioning, neutral stimuli and responses can become paired with natural experiences to create conditioned stimuli and responses (Pavlov, 1927). For example, initially, the sounds of someone cooking may not provoke any response. However, over time, someone may learn that the sounds of cooking are associated with food being made, which may induce hunger. As these associations reoccur, learning is solidified, and neutral stimuli become conditioned stimuli which provoke a learned response. Eventually, the conditioned stimuli may produce a conditioned response, even in the absence of the unconditioned stimuli (e.g., hearing someone putting dishes away may induce hunger since it sounds like cooking).

Classical conditioning plays a significant role in substance use maintenance, including marijuana use (Balter et al., 2015; Childress, 1986; Everitt & Robbins, 2005; Goddard et al., 2013). Environmental factors that occur alongside substance use often become associated over time, thus becoming conditioned stimuli. Conditioned environmental stimuli may induce psychosomatic changes, cravings, use motivation, and subjective withdrawal symptoms. For example, if an individual uses marijuana before eating dinner each night, dinner becomes paired with marijuana use, and cues that dinner is being prepared may induce cravings that promote continued marijuana use. These environmental cues may further reinforce use, as previously arbitrary stimuli are now associated with substance use and may attract greater attention (Goddard et al., 2013). Over repeated use episodes, an increasing number of cues from an individual's environment may become paired with marijuana use, thus escalating use.

One key limitation of classical conditioning is that it focuses on how a stimulus can evoke a response, however not how responses to stimuli can shape future behavior. Building on stimulus-response relations, outcomes of responses (i.e., reinforcers, punishments) can also influence future behavior. This type of learning, described as operant conditioning, was popularized by in-depth research from Skinner (e.g., Skinner, 1938).

Learning through operant conditioning focuses on how responses to stimuli (i.e., one's own behaviors) are positively reinforced, negatively reinforced, or punished (Skinner, 1938). Reinforcement follows a target behavior occurs in response to that behavior. Positive reinforcement occurs when an individual experiences a desirable response to their behavior, which serves to promote repeated behavior. Negative reinforcement occurs when individuals engage in behavior to either remove or avoid an undesirable experience from their environment (e.g., drinking alcohol to remove stress). In either case, reinforcement not only shapes behaviors in the moment, but also encourages repeated behavior over time (Ferster & Skinner, 2014). The more temporally associated a reinforcer is with a target behavior, the stronger that behavior becomes reinforced (e.g., feeling euphoric immediately after using alcohol compared to feeling hungover the next day; Ferster & Skinner, 2014). Importantly, reinforcement is unique from punishment. Punishments are negative consequences that follow behaviors and serve to reduce behavior frequency over time (Skinner, 1953). Related to marijuana use, use-related effects can be both positively (e.g., feeling elated) and negatively (e.g., use to reduce negative affect) reinforcing. Use can also be punished, as individuals may face punitive consequences following use that may reduce future use (e.g., receiving legal consequences).

While many reinforcers are objective (e.g., food, money), subjective experiences can also serve to reinforce behavior (e.g., subjective enjoyment of a drug experience, subjective stress level; Courtney & Ray, 2014). For example, feeling socially rejected may be subjectively experienced (e.g., if one interprets another's actions as rejecting without confirmation) and influential on future behavior. Marijuana use can have objectively reinforcing (i.e., stimulating biological reward) and subjectively reinforcing effects (i.e., alters perception and thinking; Everitt & Robbins, 2005; Lupica et al., 2004; Simons et al., 1998). Moreover, the perceived value of a reinforcer is often based on individual differences (e.g., personal preferences). Related to marijuana, one person may like the sedating effects of the drug, while another may not. Therefore, it can be important to measure reinforcement valence on an individual level to determine how various reinforcers shape behavior. Additionally, certain reinforcements may become devalued over time or cease to exist. When this occurs, there are reductions in the target behavior or the behavior may completely discontinue (Ferster & Skinner, 2014). However, since behavior is reinforced over time, it may similarly take time for a behavior to discontinue.

In summary, individuals learn to pair stimuli with a given response, and environmental reactions to their response (i.e., reinforcers, punishments) inform an individual's future behavior (Ferster & Skinner, 2014; Pavlov, 1927; Skinner, 1976). Applied to marijuana use, individuals often experience both positive and negative outcomes from use. If an individual has greater positive outcomes, and a stronger preference toward these outcomes, they may use on future occasions to achieve similar effects. If they have greater negative response to use, they may be hesitant to use in the future, fearing further negative effects. Incorporating timing, the effects that occur most closely to marijuana use often become more strongly associated than the effects that occur further from use (Ferster & Skinner, 2014). For example, if an individual feels elated shortly following use, then feels sleepy hours later, they may more quickly associate feeling elated with use than feeling tired.

As an individual uses over time, they may experience myriad of effects (Osborne & Fogel, 2008; Simons et al., 2012; Volkow et al., 2014). Through classical conditioning, they may learn to associate certain effects with certain environmental cues (e.g., use before a movie has positive outcomes, use before work has negative outcomes). In turn, situational cues may maintain use (e.g., starting a movie becomes a conditioned stimulus, evoking marijuana use as a conditioned response). Since certain positive outcomes may inconsistently follow use, individuals may continue to use seeking previously experienced positive outcomes, regardless of if they occur in that discreet use episode (although this is complicated by dependence, which is discussed below). This pattern is consistent with variable reinforcement, where the possibility of reward is ever-present, and results in stronger maintenance of behavior (Ferster & Skinner, 2014). If outcomes become overwhelmingly negative, or cease to be positive, the individual may discontinue use, as the stimulus-response relationship has become extinct.

Conditioning and Expectancies

As operant learning occurs, individuals begin to expect certain outcomes from their behavior. These expectations, termed outcome expectancies, develop over time and inform individuals about the probability of their behavior resulting in a given outcome (Vroom, 1964). However, social learning theory supports that substance use outcome expectancies often develop prior to actual use through social modeling (Bandura, 1977; Christiansen et al., 1982; Dunn &

Goldman, 1996; Everitt & Robbins, 2005; P. M. Miller et al., 1990). While much of the research on social learning's influence on outcome expectancies has been related to alcohol use, these patterns of learning likely apply to marijuana use as well.

As described by reciprocal determinism (Bandura, 1969), an individual's lived experience will also inform their use-related expectancies, which in turn relate to future use of that drug (Maisto et al., 1999). Expectancies that prompt continued use are based in positive or negative reinforcement. While experienced outcomes may result from a multitude of influences, including chance, individuals choose between several behavioral options based on expectancies. Applied to marijuana, an individual may use during times they expect use to result in positive, reinforcing outcomes (e.g., before a movie), or choose to abstain if an alternative behavior is more desirable (e.g., abstaining before work). Expectancies vary in terms of how likely they are to occur and how preferred the outcome is (i.e., outcome valence; Vroom, 1964). Tied to marijuana use, an individual may learn to anticipate feeling sedated or relaxed after use, which could hold a positive valence before going to sleep but a negative valence before a social event. In turn, an individual may choose to use or abstain based on what effects they anticipate and if those effects are desirable.

Broadly speaking, individuals form two types of marijuana use outcome expectancies: positive and negative outcome expectancies (Connor et al., 2011; Vangsness et al., 2005). Individuals who frequently use marijuana tend to expect greater positive outcomes (i.e., stress reduction, social facilitation, perceptual enhancement, physical effects), and place higher value on these outcomes, than those who do not use or use infrequently (Buckner et al., 2013; Linkovich-Kyle & Dunn, 2001). Similarly, holding more positive expectancies and fewer negative expectancies is associated with increased recent use, with individuals using at the heaviest rates holding the highest positive expectancies (Aarons et al., 2001; Clark et al., 2011; Linkovich-Kyle & Dunn, 2001; Neighbors et al., 2008; Pedersen et al., 2015; Vangsness et al., 2005). Positive expectancies may also be more influential than negative expectancies when predicting recent use (Boden et al., 2013; Connor et al., 2011; Hayaki et al., 2011). Conversely, holding high negative expectancies is associated with lower rates of initiation and recent use frequency (Aarons et al., 2001; Schafer & Brown, 1991; Skenderian et al., 2008; Vangsness et al., 2005). In turn, individuals who do not use or discontinue use tend to expect more negative impairments than individuals currently using marijuana (Aarons et al., 2001).

In the alcohol field, research has supported that expectancies become solidified over time and often become difficult to change (W. R. Corbin et al., 2008; Dunn & Goldman, 1996; Rather et al., 1992). Over time, marijuana outcomes may no longer match expectancies (Bonn-Miller, Vujanovic, et al., 2008). For example, chronic marijuana use to cope with distress may initially alleviate symptoms, but eventually increases emotional dysregulation and distress (Bonn-Miller, Vujanovic, et al., 2008; Bonn-Miller, Zvolensky, et al., 2008). Despite these incongruencies, the initial expectancies may continue to motivate future behavior (Vroom, 1964). If an individual experiences an unexpected outcome, they may attribute it to chance or minimize the valence rather than alter their outcome expectations (Courtney & Ray, 2014; Vroom, 1964). This attribution to chance is more likely to occur if an individual comes to strongly expect and strongly prefer a given outcome, particularly if this outcome is repeatedly experienced.

Difficulty in changing expectancies is also supported by literature on procedural knowledge (i.e., learning through experience; Willingham et al., 1989). Procedural knowledge (e.g., outcome expectancies), is harder to alter than declarative knowledge, as learning takes longer and becomes engrained patterns of behavior (Funder, 2015). Related to use, marijuana outcome expectancies that become learned over time may be difficult to alter and require repeated incongruent experiences to change (Corbin et al., 2008; Dunn & Goldman, 1996; Rather, et al., 1992).

One complicating factor in understanding how expectancies maintain use is expectancy (i.e., placebo) effects (Metrik et al., 2009). Expectancy effects have been reported to occur with marijuana use, and more so among those who use regularly (Kirk et al., 1998; Loflin et al., 2017; Metrik et al., 2009; Slavin et al., 2018). Individuals may come to highly anticipate a certain outcome to the point of subjectively experiencing the expected effect. Consistently, studies have demonstrated that cued expectancies can alter reported experienced outcomes, supporting that expectancies may influence subjective outcomes (B. T. Jones et al., 2001; Metrik et al., 2009; Slavin et al., 2018). It should be noted that only some effects of marijuana seemed susceptible to expectancy effects (e.g., decreased negative mood, stress reduction), while others did not (e.g., use satisfaction, increased positive mood; Loflin et al., 2017; Metrik et al., 2011; Metrik et al., 2009). Nonetheless, subjectively experienced expectancy effects may continue to reinforce outcome expectancies, independent of objective outcomes, and reinforce continued use.

Overall, marijuana expectancies play a significant role in understanding how marijuana use progresses from initiation to maintained use, as well as problematic use. Individuals first trying marijuana who experience rewarding outcomes may use again expecting to achieve similar outcomes. If use is not sufficiently reinforced, the individual may not continue using. Conversely, if use is reinforced, the individual will likely continue to use, and continue to expect positive outcomes from marijuana use. There may be unique reinforcing factors across individuals based on differences (e.g., preferences) that alter how use is reinforced. Therefore, it is important to examine the outcomes individuals experience to best understand the feedback loop that occurs between expectancies and outcomes. This is particularly salient among individuals with problematic use, as they often expect positive and negative outcomes from use and continue to use. The expected positive outcomes experienced among these individuals may be more influential than expected negative outcomes, however research has yet to develop measures of positive outcomes to examine their role in maintained use.

Marijuana Dependence

While learning theories provide one basis for maintained marijuana use, another important factor is dependence (Budney et al., 2007). Marijuana use indirectly stimulates reward pathways in the brain, which provides a biological incentive for repeated use (Ferland & Hurd, 2020; Tanda & Goldberg, 2003). Initially, various positive outcomes from use, including biological reward, may promote continued use. Over time, an individual's brain may become more reliant on marijuana and elicit stronger cravings for use. Approximately 9% of individuals who try marijuana develop a dependence on the drug (Volkow et al., 2014). Among these individuals, biological mechanisms may reinforce use, inhibiting the individual from objectively evaluating the outcomes and punishments from use. Those who report heavy marijuana use and those with dependence are also the most likely to be experiencing the greatest negative outcomes from use (Budney et al., 2007; Simons et al., 2012). However, these individuals may overvalue the positive aspects of use and devalue negative outcomes and punishments associated with use (Buckner et al., 2013; Clark et al., 2011; Kilmer et al., 2007; Linkovich-Kyle & Dunn, 2001).

For those with dependence, use may also become more strongly negatively reinforced. Individuals with dependence are more likely to use to cope with distressing affect (Clark et al., 2011; Dierker et al., 2018; Johnson et al., 2010). Over time, they become more likely to respond to stress with marijuana use, which may provide temporary relief. However, continued marijuana use to cope with stress often worsens mental health symptoms. Despite this iatrogenic effect, individuals with dependence often feel reliant on marijuana to cope with their distress. Moreover, regular marijuana use, especially among those with dependence, prompts stronger cravings (Filbey et al., 2009). Cravings negatively reinforce individuals by prompting more frequent use to satisfy these urges. In turn, dependent individuals may become stuck in a cycle of experiencing notable negative outcomes from use (e.g., distress, craving) and continuing to use in attempts to alleviate their negative experiences.

Despite using in part to reduce negative affect and craving, dependent individuals may frame their use as providing positive effects (e.g., helps me feel better; Johnson et al., 2010; Simons et al., 1998). While they are often aware of the negative outcomes from use, biological and behavioral mechanisms associated with dependence may provide stronger attention to the positively perceived, reinforcing aspects (Buckner et al., 2013; Clark et al., 2011; Ferland & Hurd, 2020; Linkovich-Kyle & Dunn, 2001). Among individuals with dependence, it may be particularly important to identify both the positive and negative outcomes they report, as they both may serve as important intervention targets.

Outcomes of Marijuana Use

Historically, negative outcomes of marijuana use have been the focus of marijuana research (e.g., Buckner & Schmidt, 2008; Pearson, Liese, & Dvorak, 2017; Pedersen et al., 2015; Simons et al., 2012). This research is congruent with harm reduction approaches that attempt to identify pathways to problematic outcomes. Some research has measured dependence symptoms as a proxy for overall negative outcomes of use (e.g., Buckner et al., 2015). However, negative outcomes of use have been identified that extend beyond diagnostic dependence symptoms (e.g., respiratory distress, lower motivation; Simons et al., 2012).

Several scales have been developed to measure the broad range of negative physical and mental health marijuana use-related outcomes (Pearson, 2019). Negative outcome scales often measure discrete negative outcomes (e.g., Simons et al., 2012), with some intended to generalize to a broader negative outcome construct (e.g., Martin et al., 2006). Domains of consequences measured across these scales often include social-interpersonal consequences, occupational/academic consequences, psychological consequences, physical consequences, and related risky behavior involvement (Copeland et al., 2005; Hodgins & Stea, 2018; Knapp et al., 2018; Martin et al., 2006; Simons et al., 2012). Some scales differentiate consequence severity, either through separate subscales (less and more severe factors) or based on item difficulty. Other research has also examined reported valence (i.e., "minimally" to "severely" negative) of negative consequences items (Fetterling et al., 2018); however, outcome severity (similar to expectancy valence) has yet to gain significant research attention.

Negative outcomes of marijuana use (i.e., use-related harms) are intrinsically important and gained significant research attention (e.g., Budney et al., 2007; Simons et al., 2012; Volkow et al., 2014). Studies on negative marijuana outcomes have found several factors predictive of negative outcomes (e.g., use frequency, personality facets, certain use motives; Neugebauer et al., 2019; Pearson, 2019; Simons et al., 2012). Similarly, several scales have identified various negative outcomes associated with use and other problematic life outcomes (e.g., dependence, relationship/occupational impairment). Item-level analysis has demonstrated that negative outcomes vary in degree of impairment and perceived severity (Fetterling et al., 2018; Hodgins & Stea, 2018; Simons et al., 2012). Certain negative outcomes may relate to increased life problems, while others may be relatively mild.

Related to operant conditioning and expectancy theory, individuals may balance the reinforcing effects and punishments of use based on their perceived valence of each outcome. If they develop a stronger desire for the positive outcomes, they may discount the negative effects and punishments when deciding to continue using. Research supporting this has demonstrated that individuals who use marijuana are often aware of the negative outcomes they experience and expect some of these negative outcomes to occur (Aarons et al., 2001; Simons et al., 2012). If individuals both expect and are aware of negative outcomes resulting from marijuana use, operant conditioning theory suggests that these individuals would be unlikely to continue using marijuana. However, many individuals expecting and aware of negative outcomes frequently use marijuana. Therefore, there must be positively reinforcing outcomes of use that explain maintained use in the presence of negative reinforcement. However, little marijuana research has sought to identify these outcomes.

Positive Outcomes of Use

One notable reinforcing aspect of use is marijuana use-related positive outcomes (Committee on the Health Effects of Marijuana: An Evidence Review and Research Agenda et al., 2017; Skinner, 1976). Some research has identified several objective and subjective positive outcomes of recreational marijuana use (Committee on the Health Effects of Marijuana: An Evidence Review and Research Agenda et al., 2017; Hart et al., 2010; Lyons et al., 1997; Magnan & Ladd, 2019; Osborne & Fogel, 2008; Ross et al., 2018), typically through either qualitative self-report or generally positive versus negative impressions of use effects. Additional research has also supported that marijuana use may hold positive outcomes related to medical benefits, such as reduced pain, increased appetite, and decreased nausea (Rocha et al., 2008; Volkow et al., 2014).

Positive expectancy literature provides evidence for discrete positive outcomes of use (e.g., feeling relaxed and less tense; Aarons et al., 2001). Similarly, research on marijuana use motives has identified several motivations for use that implicate positive outcomes (e.g., to feel good, to enjoy a party; Simons et al., 1998). While expectancy and motives research examine anticipated outcomes, they do not ask if these outcomes were actually experienced. Instead, they measure if each potential effect was anticipated by the participant or motivated use prior to using. Existing marijuana outcomes, expectancies, and motives studies support that several positive use-related outcomes exist and likely reinforce use. However, marijuana positive outcomes are inconsistently operationalized and measured across studies.

Despite knowledge of various positive objective and subjective experiences relating to marijuana use, a positive marijuana use-related outcomes measure, similar to the established negative outcome measures, has yet to be developed. Related to reciprocal determinism, individuals may reference experienced effects from use episodes to inform expectancies related to future use events (Maisto et al., 1999). Over time, these expectancies become established and refined by further use experiences. Individuals who experience positive outcomes from use may alter their use to continue experiencing positive effects and attempt to avoid negative outcomes. Studies examining expectancies and motives capture an important part of the learning and maintenance of use: two temporal factors that influence an individual's use behavior. However, outcome research only examining negative effects of use does not include the effects that maintain use over time. In turn, the outcomes that inform expectancies and alter future use are often left unexamined.

In the alcohol field, research has demonstrated that positive outcomes play an important role in understanding alcohol use. To date, the Positive Drinking Consequences Questionnaire

(PDCQ; Corbin et al., 2008), is the only developed positive outcomes scale for alcohol use. This 14-item measure was developed based on alcohol expectancy questionnaires, rephrasing items to reflect an experienced, rather than anticipated, outcome (e.g., “I would be outgoing” to “I approached a person I probably wouldn’t have spoken to otherwise”). Items were developed based on specific events (e.g., talked to more people than usual), rather than subjective states (e.g., felt more relaxed). Items were endorsed over the past three months on a 5-point scale measuring the frequency of each outcome from 0 to over 10 times. Further validation of this scale suggested that positive outcomes may serve as a higher-order factor, and four factors may encompass positive outcomes (Jordan et al., 2019). These four factors were sociability, tension reduction, liquid courage, and sexual enhancement; however, research has yet to examine positive alcohol outcomes using these factors. Finally, the PDCQ has also been validated among veteran and adolescent populations (Morean & Cooney, 2015; Morean et al., 2016). Psychometric evaluation of the PDCQ suggests that positive drinking outcomes may both be an inventory of discrete events, as well as an overarching latent factor.

When predicting alcohol use, positive drinking outcomes explain significant variance in alcohol use above and beyond alcohol expectancies, motives, and negative outcomes, demonstrating they are a unique and meaningful construct (Capron & Schmidt, 2012; W. R. Corbin et al., 2008; Jordan et al., 2019; Lee et al., 2011; Lorant et al., 2013; Morean & Cooney, 2015). Consistent with operant conditioning, individuals who endorse higher levels of positive outcomes (i.e., positive reinforcement) report greater levels of recent drinking, future planned consumption of alcohol, and anticipated positive outcomes (Lang et al., 2012; Logan et al., 2012; A. Park et al., 2014; C. L. Park, 2004; Patrick & Maggs, 2011). Moreover, positive outcomes may be more influential than positive expectancies and negative outcomes in predicting future drinking intentions and behavior (Lee et al., 2011; A. Park et al., 2013). This may partly due to the fact that positive outcomes often occur more closely to alcohol consumption (e.g., tension reduction) than negative outcomes (e.g., hangover), and therefore may become more strongly associated to drinking behavior (Lee et al., 2010; Skinner, 1976). Positive outcomes were a negative predictor of readiness for reducing one's alcohol consumption, similarly supporting their role in maintenance of use (Capron & Schmidt, 2012; Usala et al., 2015).

Additional research has supported that positive drinking outcomes may also be associated with greater dangerous alcohol consumption and negative outcomes of use (Capron & Schmidt, 2012; A. Park et al., 2014). Other research has found that heavy alcohol use may more severely increase negative outcomes than positive outcomes (Barnett et al., 2014). This may be particularly salient from a harm reduction perspective, as reported positive outcomes may help predict who may go on to experience greater negative consequences of use. Moreover, use of harm reduction strategies has been associated with both an increase in reported positive outcomes and decrease in reported negative outcomes (Pearson et al., 2013). Therefore, individuals may be able to learn how to alter their use-related outcomes to avoid potential harms while maintaining perceived benefits.

Clearly, positive alcohol outcomes play a significant role when understanding why individuals consume alcohol and what explains maintained use. Moreover, they relate to other significant aspects of use, including expectancies, negative outcomes, and use frequency. This is consistent with operant conditioning suggesting that positive reinforcement is key to understanding maintained behavior. Tied to negative outcomes, individuals may attempt to learn over repeated use episodes how to maximize positive outcomes of use and minimize negative outcomes. These relations have support among alcohol research; however, it is unknown if similar patterns exist among individuals who use marijuana. While a similar overarching theory may apply to marijuana use, the aspects of use perceived as reinforcing, as well as how to measure them, are still understudied.

Scale Development

When developing a psychological measurement scale, psychometric theory and research can be used to provide guidance (Boateng et al., 2018; DeVellis, 2012; Raykov & Marcoulides, 2011). First, it is important to identify the domain and construct that is intended to be measured and the purpose of the scale. Some scales intend to be an inventory of discreet responses, where endorsement of each item holds unique significance (e.g., depression symptoms), while other scales intend to generalize to a latent construct (e.g., personality scales). Several substance use related scales are a hybrid measurement, as their discreet items are uniquely meaningful, and scale scores intend to generalize to latent factors (e.g., MACQ, PDCQ). In these scales, item-level and scale/subscale scores are used to inform research and intervention.

Measuring positive outcomes will likely function through a similar framework. Identifying discreet positive outcomes will give meaningful information about the unique outcomes one experiences that reinforce their use. Overall scale scores will generalize to an overarching positive outcome construct, informing how generally positive one experiences marijuana outcomes. This may also apply to subscales, or factors, or positive outcomes, where there may be variability in latent aspects of use. For example, on the PDCQ, an individual may generally experience positive alcohol sociability outcomes, but not experience positive sexual outcomes related to use.

Next, item generation is a crucial aspect of scale development. There are two methods for generating items: reviewing previous literature and theory (deductive method) and consulting with individuals with whom the scale will be used (inductive method; Boateng et al., 2018). It is considered best practice to combine these methods, as this will provide the most comprehensive coverage of the intended construct. Related to positive outcomes, previous research has identified several positive outcomes associated with use and individuals who use marijuana can also provide qualitative responses about positive outcomes they have previously experienced. Specific item wording and content should reflect construct of interest, with extraneous or tangential items being excluded from the initial item pool (Boateng et al., 2018; DeVellis, 2012). Good scale items are succinct, specific, easily understood, and unambiguous. It is important to initially write at least double the number of items than included in the final scale. Additionally, generating semi-redundant items may be beneficial, as this may help distinguish the best way of measuring a specific aspect of a construct (DeVellis, 2012). Once developed, the initial item pool should be evaluated by experts to ensure they are adequate, comprehensive, appropriate, and reflect the domain of interest (Boateng et al., 2018).

After items are generated, a response scale should be picked that matches the intended purpose of the scale. For scales measuring latent constructs, Likert-style response scales are often used, as they can provide continuous construct coverage (Boateng et al., 2018). Likert-style scales can be bipolar (e.g., negative to positive) or unipolar (e.g., never to always). Research has examined how to maximize the reliability and information from Likert scales based on the number of response options. One primary consideration is whether to include a scale midpoint (i.e., neutral/central option) or to use an even number of items and force respondents to pick a side of the continuum. One study examining scale error suggested that exclusion of a midpoint results in respondents randomly selecting a moderate response that approximates a neutral response, and inclusion of a midpoint can reduce error and improve reliability for Likert scales

(O'Muircheartaigh et al., 2000). When deciding the number of response options, studies have demonstrated negligible improvement in reliability and information when including more than seven response categories (Cicchetti et al., 1985; Green & Rao, 1970). For bipolar scales, some studies suggest reliability is maximized with seven response options (Finn, 1972; Nunnally, 1967; Oaster, 1989; Ramsay, 1973), while others support that five response options may have higher reliability (Jenkins & Taber, 1977; McKelvie, 1978). Selecting between five and seven categories should be based on the intended use of the scale and clarity (DeVellis, 2012; Krosnick & Fabrigar, 1997). Unipolar scales are suggested to have five response categories.

After finalizing the initial item pool and response scale, the scale should be administered to the target population (Boateng et al., 2018). Several suggestions have been made to establish an adequate sample size for conducting factor analysis on the scale. Some research suggests including no fewer than 3 participants per scale item, with an ideal of 10 participants per item (Velicer & Fava, 1998; Worthington & Whittaker, 2006). Other research notes that the total sample size may be more important that the number of participants per item, and suggests including at least 300 and ideally 500 participants (Boateng et al., 2018; Worthington & Whittaker, 2006). Since there is no established consensus, researchers should target having a larger sample size to help reduce error and establish more stable factors. Importantly, if researchers intend to conduct exploratory and confirmatory factor analysis, they must collect sufficient data for each analysis, as the same data cannot be used for both (DeVellis, 2012).

When evaluating scales, many common analyses are based in classical test theory, which assumes that items are indicators of a latent construct, and that the observed scores are a combination of a "true" score on the underlying construct and random error (DeVellis, 2012). Once data has been collected, initial analyses can be conducted to determine which items should be maintained and which should be removed. First, item-level examinations (e.g., means, variance) should determine response distributions, as heavily skewed items may function poorly with other scale items and be poor construct indicators (DeVellis, 2012). Inter-item and item-scale correlations should also be examined, as uncorrelated items are likely not measuring the same construct as other scale items (Boateng et al., 2018; DeVellis, 2012). Factor analysis can then be conducted to determine scale dimensionality, the variance each item shares with the underlying construct, establish the number of scale factors, and remove unnecessary items (DeVellis, 2012). Factor analysis uses rotation to simplify data and help establish unique factors. Orthogonal rotation is used when factors are expected to be uncorrelated and oblique rotation is used when factors are expected to be correlated. The rotation method is specified prior to conducting factor analysis.

When conducting exploratory factor analysis (EFA), eigenvalues, the scree plot, parallel analysis, model fit, factor loadings, and internal consistency are used to determine the number of factors and item retention (Costello & Osborne, 2005; DeVellis, 2012). Eigenvalues greater than 1 can help determine the maximum number of values, however, may be an overestimate of the true number of factors (Floyd & Widaman, 1995). Another indicator of the number of factors is when the slope of the scree plot, a graphic representation of eigenvalues, approaches 0. Additionally, parallel analysis conducts factor analysis on generated random data, which can then be used to determine the number of stable factors within the observed data (DeVellis, 2012). Eigenvalues from the observed data greater than eigenvalues from the parallel analysis are likely stable factors.

Once the likely number of factors has been established, factor loadings (i.e., slope coefficients associating the item with the underlying factor) are examined to determine item retention. Items with factor loadings below 0.32 contribute little variance to the factor and should be removed (Boateng et al., 2018). Items that have notable factor loadings on two or more factors (i.e., cross-loadings; loads >.32 on two or more factors; DeVellis, 2012) should also be removed, as they do not provide unique variance for one factor. Model fit, or measures of how well the estimated model predicts the observed data, is also used to determine the factor structure. EFA model fit indices typically include chi-square, standardized root mean square residual (SRMR), and comparative fit index (CFI; Hu & Bentler, 1999). EFA is an iterative process, where results are evaluated, items are removed, and EFA is conducted again. Often more stringent factor loadings (e.g., 0.4 to 0.7; Tabachnick & Fidell, 2019; Worthington & Whittaker, 2006) are used to further reduce scale items.

Internal consistency, a measure of reliability, should also be examined to ensure all items within each factor covary relative to the factor total score and contain minimal error (Boateng et al., 2018). Cronbach's α is a common measure of internal consistency; however, research has supported that McDonald's ω may provide a more accurate, stable estimation of reliability (Revelle & Zinbarg, 2008). Final scale items should be parsimonious and have good internal consistency (Boateng et al., 2018). The final EFA model should have good fit, good factor loadings, and no cross-loadings. Established factors should make theoretical sense and items within each factor should have related content.

Once a final EFA model is established, a confirmatory factor analysis (CFA) should be conducted in a different sample to determine the stability of the established factor structure (DeVellis, 2012). Sample size is determined by similar estimations used in EFA. In CFA, items are specified to hypothesized factors, then factor loadings and model fit are examined to evaluate the factor structure. Factor loadings and internal consistency are evaluated with the same criteria as EFA. CFA model fit is typically evaluated using chi-square, root mean square error of approximation (RMSEA), and CFI indices.

While factor analysis can be used to determine if scale items have shared variance with a common underlying factor, it does determine if the scale is measuring the construct it intends to measure (DeVellis, 2012). Different types of validity testing must be conducted to establish the measured construct. Through each validity test, researchers can establish under what conditions the scale functions as intended (Boateng et al., 2018). Common types of validity testing include content validity, criterion validity, and construct validity, although other types of validity may be evaluated depending on the intended purpose of the scale (DeVellis, 2012).

Content validity is established during item generation by evaluating if the scale comprehensively contains the appropriate content necessary to measure the underlying construct. Criterion validity is established by evaluating the degree to which the new scale is associated with other measured variables that it should theoretically be related to (Boateng et al., 2018). To do this, researchers can use the scale to predict future behavior (i.e., predictive validity) or test the scale's relation to a concurrently measured criterion (i.e., concurrent validity). For example, measures of intentions to use marijuana among individuals currently using the drug should predict frequency of use over the following month (i.e., predictive validity) and in the past 30-days (i.e., concurrent validity).

Construct validity is commonly established by examining convergent validity and discriminant validity (Boateng et al., 2018; DeVellis, 2012). To evaluate convergent validity, the scale is compared to other established scales measuring similar constructs to determine the degree to which they relate. For example, new measures of marijuana expectancies should relate to established expectancy and outcome scales. Discriminant validity examines the degree to which the new scale is differentiated from related but distinct constructs to ensure it is not an alternative measure of the same construct (Boateng et al., 2018). A related example could be differentiating between expectancies and outcomes, as there is theoretical basis for differences between these constructs. Newly developed scales should not be too highly related to existing measures of related but distinct constructs, which can be examined using scale correlations. While the exact types of scale validation depend on the intended purpose of the scale, establishing validity is crucial for understanding under what conditions the scale functions as intended.

Using rigorous methods to develop and evaluate new measurement scales will best establish useful instruments. Following established methods for generating items, collecting data, evaluating factors, and establishing validity will best develop a new scale to measure positive marijuana outcomes.

The Present Study

With recent increases in recreational legalization of marijuana use increasing access to marijuana (J. Jones et al., 2018; National Organization for the Reform of Marijuana Laws, 2019), it may be more important than ever to understand the aspects of use that are positively reinforcing and predict maintained use. Doing so may help inform harm reduction approaches that can intervene prior to or reduce already occurring problematic outcomes of use. Since positive alcohol outcomes have shown significant relations to future use, negative outcomes, and problematic use, similar associations should be investigated among marijuana use outcomes. Individuals who experience greater positive marijuana outcome may be likely to use more frequently, and in turn, experience greater negative outcomes. By identifying positive outcomes of marijuana use and related associations, policy makers, clinicians, and individuals using marijuana may be able to guide marijuana use toward times that minimize harms of use and intervene or find replacement behaviors for identified positive outcomes.

The present designed and psychometrically evaluate a marijuana use-related positive outcomes measure. Based on previous marijuana and alcohol literature (e.g., expectances, identified outcomes), as well as qualitative responses from a pilot survey, items were generated measuring social outcomes, stress reduction and psychological effects, sexual enhancement, and physiological outcomes. As part of the psychometric evaluation, factor structure, reliability, and validity were examined. The scale was evaluated among college students and adults from the community who recreationally use marijuana. Invariance testing was conducted between these populations to determine if the scale was comparable between populations. I hypothesized that:

1. Marijuana use-related positive outcomes would be positively associated with marijuana use, positive expectancies, and negative outcomes.
2. Marijuana use-related positive outcomes would be unrelated to alcohol use.
3. Marijuana use-related positive outcomes would be unrelated to positive alcohol outcomes.
4. Marijuana use-related positive outcomes would account for unique variance when predicting recent use, controlling for expectancies and negative outcomes.

STUDY 1

Method

Participants and Procedure

College students who reported past 30-day marijuana use were recruited from psychology courses. Students (N = 906) completed a survey measuring marijuana-use related constructs, as well as other necessary information. Seven participants were removed due to concerning response patterns (e.g., selecting the same response number across multiple questionnaires) and thirteen were removed for excessive missing Positive Outcomes Scale for Marijuana (POSM) data (see Analysis section). Data were collected during the Spring and Fall 2020 semesters. Participants included in analysis (N = 883) were 63.4% female, had a mean age of 19.98 (SD = 2.72), were 81% White, and were 77.2% non-Hispanic (full demographics are presented in Table 1). Data were collected via online computerized surveys that participants completed on their own devices. Participants received course credit in exchange for study participation. The study was approved by the university institutional review board and all participants consented to participation.

Measures

Participants reported demographics including age, sex, gender, race, ethnicity, and sexual orientation. Marijuana and alcohol use were assessed by asking participants on how many days they used each substance in the past 30 days. Marijuana use frequency was also measured by dividing each week into 42 time periods (i.e., Monday through Sunday: 12am-4am, 4am-8am, 8am-12pm, 12pm-4pm, 4pm-8pm, 8pm-12am) and asking participants to select the time periods they had typically used during the past three months (i.e., typical use frequency; Pearson et al., 2017). A sum was generated from the endorsed time periods to measure typical use frequency.

Table 1
Participant Demographics and descriptive statistics

	College Sample (N = 883)		Community Sample (N = 213)	
	M	***SD***	***M***	***SD***
Age	19.98	2.72	35.74	8.92
Sex	***N***	***%***	***N***	***%***
Male	319	36.1	115	53.7
Female	560	63.4	97	45.3
Not Specified	4	0.4	2	0.9
Gender				
Man	299	33.9	111	51.9
Woman	540	61.2	92	43.0
Transgender	3	0.3	4	1.9
Otherwise specified	30	3.4	6	2.8
Not specified	11	1.2	1	0.5
Race				
American Indian	15	1.7	-	-
Asian	26	2.9	6	2.8
African American	22	2.5	1	0.5
Hawaiian/Pacific Islander	2	0.2	-	-
White	715	81.0	194	91.5
Other	41	4.6	-	-
Multiracial	61	6.9	5	2.3
Not Specified	1	0.1	8	3.7
Ethnicity				
Hispanic or Latino	158	17.9	10	4.7
Not Hispanic or Latino	682	77.2	197	92.9
Not Specified	43	4.8	7	3.3
Sexual Orientation				
Exclusively Heterosexual	512	58.0	112	52.3
Mostly Heterosexual	152	17.2	43	20.1
Bisexual	82	9.3	17	7.9
Mostly Gay/Lesbian	52	5.9	15	7.0
Gay/Lesbian	52	5.9	19	8.9
Asexual	8	0.9	1	0.5
Pansexual	17	1.9	5	2.3
Not Specified	8	0.9	2	1.0

Note: College age range 18.04-57.98, Community age range 22.80-69.99

Marijuana expectancies were measured using the Marijuana Effect Expectancy Questionnaire-Brief (MEEQ-B; Torrealday et al., 2008), which has previously been used college samples (e.g., Berey et al., 2021; Brackenbury et al., 2016). The MEEQ-B is a six-item, Likert-style measure that assesses two subscales: positive and negative expectancies. Participants rated each item by how much they expect each effect to occur from "Strongly Disagree" to "Strongly Agree." Expectancy subscales are scored by taking a mean of the three subscale items. Reliability in this sample, positive $\alpha = .77$ and negative $\alpha = .30$ in this sample, was similar to the initial scale validation study (positive $\alpha = .60$ and negative $\alpha = .42$; Torrealday et al., 2008) and a college student sample (positive $\alpha = .61$ and negative $\alpha = .40$; Brackenbury et al., 2016).

Negative use-related outcomes were measured using the Brief Marijuana Consequences Questionnaire (B-MACQ; Simons et al., 2012). The B-MACQ includes 21 dichotomous negative outcomes related to social-interpersonal consequences, impaired control, self-perception, self-care, risk behaviors, academic/occupational consequences, physical dependence, and blackout use. B-MACQ responses were scored as a sum of the number of consequences a participant endorsed experiencing ($\alpha = .85$ in this sample).

Positive drinking outcomes was measured using the PDCQ (W. R. Corbin et al., 2008). The PDCQ measured 14 discrete positive outcomes associated with alcohol use ($\alpha = .95$ in this sample). Participants select the number of times each outcome occurred over the past month across an ordinal scale ("0," "2-3," 3-5," "6-10," ">10"). To create a total scale score, I calculated a mean of PDCQ scale items.

Finally, participants completed the POSM (see Appendix C for the final scale). The initial POSM items were developed based on responses to qualitative responses from other studies about use-related positive outcomes participants had experienced and positive outcomes identified in previous research (e.g., Aarons et al., 2001; Metrik et al., 2009, 2011; Osborne & Fogel, 2008; Simons et al., 1998). In previous research studies, participants responded to the question: “Please list up to 3 positive outcomes you have experienced because of your marijuana use.” College students who reported marijuana use (N = 657) provided 1,745 qualitative responses and adults from the community who reported marijuana use (N = 73) provided 213 qualitative responses (parent study: Prince et al., 2018). Qualitative item generation followed similar methods to previous research (J. M. Corbin & Strauss, 1990; O’Neill & Sevastos, 2013). After all items were compiled, ambiguous items were removed. Initially, items were sorted by broadly related themes (e.g., social, mood, sleep). Next, overly redundant items were removed (e.g., “sleep better,” “better sleep”), and remaining items were further sorted into subgroups for each theme (e.g., sleep was divided into improved sleep initiation, sleep length, sleep quality, and feeling rested). From the final subgroups, I generated discrete items to capture the distinct themes and aspects of the qualitative responses (e.g., “I slept longer than I normally do”). Qualitative responses ultimately generated seventy-seven items.

Next, I reviewed previous literature identifying positive aspects of marijuana use (e.g., positive expectancy scales, motives scales, research on subjective marijuana effects, research on perceived benefits of use) to determine if any additional identified outcomes were missing from the qualitative responses. This literature review resulted in four additional items that were not captured by the qualitative responses. In total, I wrote eighty-one initial items, which were approved by the doctoral dissertation committee who have marijuana research expertise. Given that most negative outcome scales range from 19 to 58 items (Copeland et al., 2005; Hodgins & Stea, 2018; Knapp et al., 2018; Martin et al., 2006; Simons et al., 2012; Stephens et al., 2000) and the PDCQ contains 14 items, 81 initial items were sufficient for a final scale containing up to approximately 40 items (Boateng et al., 2018).

Each POSM item included three Likert-style response scales: frequency, valence, and influence on future use. Frequency of occurrence was rated from "never" to "always," valence was rated from "negative" to "positive," and influence on future use was rated from "not at all influential" to "highly influential." Item order was randomized for each participant reducing potential ordering effects and influence from items on each other (Schell & Osward, 2013; Strack, 1992). The POSM instructions read:

> Think about the outcomes you have experienced when using marijuana in the past month. When responding to each item, please respond with:
>
> - How often the outcome has actually occurred for you after using marijuana in the past month.
> - Rating how positive or negative the outcome typically was for you.
> - Rating how likely it is that the outcome will influence your future marijuana use.
>
> After using marijuana…

Analysis

Analyses were conducted using SPSS 27.0, MPlus version 8.5, and R version 4.0.5 (IBM, 2020; Muthén & Muthén, 2020; R Core Team, 2021). Positive outcome frequency served as the primary POSM analysis scale, as it measured rate at which outcomes were experienced. Outcome valence and influence on future use served as supplemental scales to aid in scale development and may inform future, follow-up analyses. During initial scale evaluation, I examined individual item characteristics. First, I examined item response frequencies and removed items with limited endorsement ranges (e.g., all responses were "almost always" and “always”) rates. Next, I examined mean item valence for each scale item. Items with scale means of “negative” or “slightly negative” were removed, as the POSM is a positive outcome scale. Finally, I examined mean item influence. Items with a mean of “not at all influential” or “slightly influential” were removed, as these were likely unimportant outcomes.

For remaining scale items, I calculated item-level correlations and item-total correlations for outcome frequency ratings. Correlations were examined for items that held mixed positive and negative correlations or mostly negative correlations with other items or the total score. Items with positive correlations with other items and the item-total score were retained.

Prior to conducting EFA, I examined the missingness and distributions of the remaining items. While EFA is robust to missing data (Muthén & Muthén, 2020), large amounts of missing data may impact the factor structure and model fit (Tabachnick & Fidell, 2019). Therefore, participants missing more than 50% of the remaining POSM items were removed prior to analyses. While missing completely at random is preferred, maximum likelihood estimation (MLE) can accommodate data missing at random (McNeish, 2017). If item missing data is less than 5%, it can often be ignored and considered missing at random (Buuren, 2018; Tabachnick & Fidell, 2019). Since the remaining scale items violated the assumption of multivariate normality, maximum likelihood estimation with robust standard errors (MLR) was used. MLR uses the sandwich estimator to compute standard error estimates, which is based on the observed residual variance rather than assuming independent, parametric residual variance (Geyer, 2013; Muthén & Muthén, 2020). Making this adjustment can account for unequal residual variance across items and obtain a more accurate estimate of standard errors.

The analytic sample was randomly divided in half to develop an EFA and CFA sample (Fabrigar et al., 1999). The resulting sample size should contain at least 300 participants and more than 3 participants per item (Worthington & Whittaker, 2006). To ensure the samples were balanced (DeVellis, 2012), I calculated Pearson's chi-square to test for age differences, a T-test was conducted to test for age differences, and conducted quasi-Poisson regression to examine differences in past 30-day use (Baggio et al., 2018).

EFA was then conducted in the EFA sample. Since all item-level and item-total correlations were positive, any identified factors were also expected to be correlated. Accordingly, EFA was conducted using oblique rotation (DeVellis, 2012). I conducted and evaluated several successive EFAs by examining eigenvalues, the eigenvalue scree plot, parallel analysis, model fit, and factor loadings/cross-loadings (DeVellis, 2012). Eigenvalues greater than one, the scree plot slope, and parallel analysis eigenvalues were used to establish the likely number of stable factors (DeVellis, 2012). Using these criteria, the most likely number of factors present in the data was determined. When examining items within each factor, factors with less than three items were considered unstable (Costello & Osborne, 2005). Therefore, if model results suggested a factor with less than three items, I considered an EFA solution with one fewer factors.

After the number of factors was determined, model fit and factor loadings were evaluated. For model fit, I used SRMR < .07, and CFI > .94 (CFA > .90 is adequate) as cutoff criteria to establish excellent fit (Hu & Bentler, 1999; Kenny, 2020). While a non-significant chi-square is often used to establish model fit, chi-square significance is highly influenced by sample size. Therefore, excellent fit can be established with a significant chi-square if other fit statistics met cutoff criterial. When examining factor loadings, items with loadings below .32 were considered poor indicators and were removed (Tabachnick & Fidell, 2019). Similarly, I removed items with cross-loadings above .32. Once items were removed, I conducted a subsequent EFA with remaining scale items. If model fit was still poor, more stringent minimum factor loadings (e.g., .40, .50) were used to remove additional items and consolidate factors.

The final factor structure was established once all poorly loading and cross-loading items were removed, and excellent model fit was achieved. I then McDonald's ω for each factor to evaluate internal consistency, a measure of reliability (McDonald, 1999). Similar to other reliability coefficients, ω > .70 indicated acceptable reliability, ω between .80 and .95 indicated excellent reliability, and ω > .95 indicated the factor contained redundant items and should be further consolidated (Boateng et al., 2018). If factors demonstrated poor or excessive reliability, I considered removing additional items. Once excellent reliability was established, the items within each factor were examined for related content. I then compared the factor item content to existing literature, interpreted, and given a salient label (DeVellis, 2012).

CFA evaluated the factor structure established in EFA demonstrated acceptable fit for the CFA sample. I established excellent model fit based on CFI > .94 (> .90 is considered adequate) and root mean square error of approximation (RMSEA) < .08 (RMSEA < .05 is adequate fit; Hu & Bentler, 1999; Kenny, 2015; MacCallum et al., 1996). Standardized factor loadings were evaluated to ensure they were above the .32 cutoff. If the resulting model fit was poor or items had low factor loadings, I removed poorly loading items and conducted additional CFA. Additionally, I considered utilizing modification indices to improve model fit (Muthén & Muthén, 2020). Modification indices identify items that have high residual correlations, which can reduce overall fit. Therefore, if two items within the same factor had a high modification index, the item with the lower factor loading was considered for removal (Whittaker, 2012). Once the CFA demonstrated acceptable model fit, no further adjustments were necessary. I then used ω to evaluate factor internal consistency.

POSM development was initially conducted in Study 1, then further refined in Study 2. Once I completed model adjustments in Study 2, I re-evaluated the final Study 2 factor structure in the Study 1 CFA sample. If this factor structure still demonstrated excellent fit, acceptable loadings, and excellent reliability, I considered this the final version of the scale. I then used the final scale version for validation and hypothesis testing in Studies 1 and 2.

Based on results from the PDCQ that suggested scale factors loaded onto a higher order positive drinking outcomes factor, I conducted supplemental analysis to determine if identified POSM factors loaded onto a higher order factor. To test this, a CFA model was estimated including an additional latent factor defined by the identified POSM factors. I evaluated the resulting model fit to determine if a higher order factor was supported by the estimated model.

Since all model factors were expected to be correlated and may load onto a higher order factor, I calculated a total scale score to perform validation analyses and test the study hypotheses (DeVellis, 2012). All analyses were developed a prior and I used $\alpha < .05$ to determine significant differences. For all count-distributed outcome variables, I considered using Poisson, negative binomial, and quasi-Poisson models (Baggio et al., 2018; Gelman & Hill, 2007). If a variable's distribution appeared to fit a Poisson distribution, a Poisson model was estimated, then I calculated an overdispersion ratio using the Performance R package (Lüdecke et al., 2021). If the overdispersion ratio was significantly different than 1 using a chi-square test, the model was deemed overdispersed, and I used negative binomial regression instead. If the count distribution appeared to fit neither Poisson nor negative binomial distributions (e.g., due to skew, outliers), then I used quasi-Poisson regression. I calculated incidence rate ratios (IRR) from count model parameter estimates to describe the rate at which the predictor influences the outcome variable (i.e., percentage increase in the outcome per one-unit increase in predictor variable; Hilbe, 2014).

Pseudo R^2 estimated changes in variance in negative binomial hierarchical regression models using the DescTools R package (Signorell, 2021). The Veall-Zimmermann pseudo R^2 most closely resembles the ordinary least squares (OLS) R^2 and was interpreted as a percent of variance in the outcome accounted for by the model (Smith & McKenna, 2013; Veall & Zimmermann, 1994). However, the Veall-Zimmermann pseudo R^2 was unavailable for quasi-Poisson regression models. For those models, only Efron's pseudo R^2 could be calculated (Efron, 1978; Signorell, 2021), which often underestimates the true OLS R^2 (Langer, 2016; Smith & McKenna, 2013), and is not appropriate for comparing multivariate regression models (Laitila, 1993). In turn, pseudo R^2 was not calculated for quasi-Poisson models.

To test concurrent validity, I regressed past 30-day use on POSM scores. I tested convergent validity by using the MEEQ-B positive expectancies factor to predict POSM scores. Since individuals who use more often report greater negative outcomes, I also tested convergent validity using POSM scores to predict negative outcomes of use. Discriminant validity was tested by regressing past 30-day alcohol use on POSM scores. Additionally, PCDQ scores were regressed on POSM scores, as these were also expected to be unrelated. To test for incremental validity, I used hierarchical regression. In the first step, MEEQ-B subscales and B-MACQ scores predicted past 30-day use. In the second step, POSM scores were added. Since pseudo R^2 is unavailable for quasi-Poisson regression, I was unable to determine the change in variance associated with adding POSM in the hierarchical models testing past 30-day use. Instead, I examined changes in how each variable predicted use to describe POSM's influence on model prediction.

Since I observed that past 30-day use had ceiling effects among individuals reporting daily use, I conducted supplemental analyses using the typical use frequency variable. This variable had greater variability and could better distinguish differences in use patterns. First, typical use frequency was regressed on POSM scores. Next, the hierarchical regression model was repeated using typical use frequency as the outcome. I examined pseudo R^2 change to determine the change in variance accounted for by adding POSM scores.

Results

Means and standard deviations for all study variables are presented in Table 2. POSM items distributions and endorsement rates were examined across the frequency, valence, and influence scales. From these initial evaluations, I removed 16 items. Item-level correlations and item-total correlations were calculated for outcome frequency ratings among remaining scale items. Interestingly, all 65 remaining items had small to large, positive correlations with the remaining items and total scale score, and thus were all maintained.

Table 2
Descriptive Statistics for Study Variables

	College Sample		Community Sample	
	M	***SD***	***M***	***SD***
Past 30-day Marijuana Use	11.57	10.80	23.36	9.85
Past 30-day Alcohol Use	6.77	6.58	7.57	8.35
Typical Marijuana Use Frequency	7.31	7.77	16.89	10.78
B-MACQ	4.64	4.13	4.32	3.41
MEEQ-B: Positive	4.06	0.76	4.43	0.46
MEEQ-B: Negative	3.21	0.68	2.73	0.73
PDCQ	2.08	0.90	1.50	0.58
POSM	3.03	0.81	3.41	0.73

Note: Brief Marijuana Consequences Questionnaire (B-MACQ), Marijuana Effect Expectancy Questionnaire – Brief (MEEQ-B), Positive Drinking Consequence Questionnaire (PDCQ), Positive Outcomes Scale for Marijuana (POSM)

I used the remaining sixty-five items in EFA. Missing data on the EFA POSM items ranged from 0.2% to 2.2%, which is considered ignorable missing data and can be assumed to be missing at random (Buuren, 2018; Tabachnick & Fidell, 2019). After randomly dividing the analytic sample, the resulting samples (n = 442 for EFA, n = 441 for CFA) were a sufficient size for factor analysis. The EFA and CFA samples were not significantly different by sex (χ^2 = 1.37, df = 3, p = .71), age (t = .20, df = 854, p = .84) or past 30-day marijuana use (b = -0.03, SE = 0.06, p = .62).

In the initial EFA, eigenvalues, the scree plot, and parallel analysis suggested there were likely four factors within the data. The model demonstrated adequate fit, χ^2 = 3,267.92, df = 1,826, p < .001, CFI = .90, SRMR = 0.04. When evaluating items within the four-factor model, fifteen items had factor loadings below .40 or had significant cross-loadings (i.e., >.32 on multiple factors) and were removed from the item pool. The remaining fifty items uniquely loaded onto the four factors. I conducted a second EFA using these fifty items, with eigenvalues, the scree plot, and parallel analysis continuing to suggest a four-factor solution. Model fit had improved, however, still did not reach excellent criteria (χ^2 = 1,949.11, df = 1,031, p < .001, CFI = .92, SRMR = 0.03). When evaluating the items, I increased the factor loading cutoff criteria to .50 to remove additional items and the .32 criteria was maintained for cross-loadings. I ultimately removed four items from the pool, leaving forty-six for the subsequent EFA.

Results from the third EFA iteration continued to suggest a four-factor solution, which had adequate model fit (χ^2 = 1,563.74, df = 857, p < .001, CFI = .93, SRMR = 0.03). When evaluating items, I applied the same factor loading (.50) and cross-loading (.32) cutoff criteria, which resulted in five items being removed. Since model fit was still below the target criteria, I conducted a fourth EFA. This EFA also suggested a four-factor solution, with improved, nearexcellent fit, χ^2 = 1,184.41, df = 662, p < .001, CFI = .94, SRMR = 0.03. Applying the same item-level criteria, I removed three more items from the scale. As with previous models, the fifth EFA suggested a four-factor solution, and had similar model fit (χ^2 = 1,022.53, df = 557, p < .001, CFI = .94, SRMR = 0.03). Seeking to remove additional items and improve fit, I raised the factor cutoff criteria to .60, which resulted in the removal of nine items.

The twenty-nine remaining items were included in a final, sixth EFA. The eigenvalues, scree plot, and parallel analysis continued to suggest a four-factor solution. The four-factor solution demonstrated excellent model fit, χ^2 = 515.36, df = 296, p < .001, CFI = .96, SRMR = 0.02. Factor loadings ranged from .54 to .91, with no significant cross-loadings (see Table 3). The fourth factor only contained two items, which is often considered unstable (Costello & Osborne, 2005). However, the content of these items was highly interrelated (sexual experience), unique from other factors, had high factor loadings (0.96, 0.75), were supported by theory (e.g., previously identified marijuana outcomes, a factor on the PDCQ), and this factor had been stable since the start of the EFA modeling. I theorized that if additional sexually related items were included in the initial item pool, they would help stabilize this factor and result in a unique, distinct factor. In turn, I opted to maintain this factor. All four factors demonstrated excellent reliability: factor 1 ω = .87, factor 2 ω = .94, factor 3 ω = .91, and factor 4 ω = .89. When examining the content of each factor and comparing it to previous research, the four factors that emerged were Social Enhancement, Mood Enhancement and Relaxation, Perceptual Enhancement, and Sexual Enhancement.

Table 3
Exploratory Factor Analysis Factor Loadings (Geomin Rotated)

	Factor 1	Factor 2	Factor 3	Factor 4
I was more vulnerable with others than I normally am.	**0.60**	0.02	0.01	0.10
It felt easier than normal to be open with others.	**0.70**	0.15	-0.08	0.07

It was easier for me to make conversation when I usually would have talked less.	**0.74**	0.06	0.11	-0.06
I talked to someone new in a situation where I usually would have kept to myself.	**0.66**	-0.06	0.15	0.05
I felt more comfortable in social situations than when I am sober.	**0.75**	0.10	0.03	-0.06
I was able to fall asleep faster.	-0.01	**0.58**	-0.08	0.11
I enjoyed the feeling of being high.	-0.09	**0.77**	-0.03	0.04
I felt more content than I normally do.	0.21	**0.55**	0.08	0.07
It was easier to ignore things that were already bothering me.	0.09	**0.54**	0.15	-0.01
I felt less tense and stressed.	0.12	**0.73**	-0.02	-0.06
I felt calmer than before getting high.	0.11	**0.61**	-0.02	0.06
It was easier to distract myself from stressful thoughts.	0.09	**0.74**	0.05	-0.06
My mood improved.	0.06	**0.74**	0.09	-0.07
I had fewer worries than before I got high.	0.21	**0.57**	-0.02	0.08
It was easier for me to have a positive outlook.	0.13	**0.60**	0.17	0.04
Arts, music, and movies were more enjoyable while high.	-0.04	**0.60**	0.12	0.12
I felt less bored after using marijuana.	-0.01	**0.63**	0.13	0.07
I felt more relaxed.	-0.06	**0.87**	-0.05	-0.06
I had more energy to stay active.	0.08	-0.07	**0.76**	0.00
It was easier to focus on the task at hand.	-0.05	0.10	**0.73**	-0.07
It was easier to begin tasks that usually are hard for me to start.	0.10	0.05	**0.72**	0.00
I solved a problem I had been struggling with.	0.04	0.02	**0.63**	0.08
I found a creative solution to a problem I usually find difficult.	-0.02	0.13	**0.61**	0.10
I felt more awake and alert.	0.14	-0.10	**0.69**	-0.04
Tasks I usually find boring I felt excited to do.	0.00	0.18	**0.63**	0.05
I felt more excited do housework, chores, etc.	-0.14	0.12	**0.80**	-0.02
I was able to work out harder/longer than I can when I am sober.	0.04	-0.23	**0.73**	0.10
A sexual experience felt more intense.	-0.01	0.03	0.00	**0.96**
A sexual experience felt more enjoyable than when I am sober.	0.09	0.02	0.08	**0.75**

CFA evaluated the factor structure found within EFA. The model demonstrated adequate fit, $\chi^2 = 733.25$, df = 371, p < .001, CFI = .93, RMSEA = .047 (90% CI .042-.052). Standardized factor loadings ranged from .51 to .91. All four factors continued to show excellent reliability: factor 1 ω = .84, factor 2 ω = .93, factor 3 ω = .91, and factor 4 ω = .87. Since this model demonstrated adequate fit, no further changes were made, and these items were retained for Study 2. Following the removal of twelve items in Study 2, a second CFA evaluated the factor structure from the Study 2 final CFA. Model fit improved in this model, and it achieved excellent fit, $\chi^2 = 174.95$, df = 113, p < .001, CFI = .96, RMSEA = .035 (90% CI .025-.045). Standardized factor loadings ranged from .69 to .91 (see Table 4), and all four factors demonstrated excellent reliability (factor 1 ω = .84, factor 2 ω = .86, factor 3 ω = .86, and factor 4 ω = .87). Supplemental analysis supported the presence of a higher order factor, as demonstrated by excellent model fit, $\chi^2 = 185.13$, df = 115, p < .001, CFI = .97, RMSEA = .037 (90% CI .027-.047). All scale factors significantly loaded onto the higher order factors (standardized factor loadings: 0.79, 0.79, 0.83, 0.54, respectively).

Table 4

Confirmatory Factor Analysis Standardized Factor Loadings and Descriptive Statistics

	College Sample	Community Sample
Factor 1		
It felt easier than normal to be open with others.	.70	0.78
It was easier for me to make conversation when I usually would have talked less.	.81	0.78
I talked to someone new in a situation where I usually would have kept to myself.	.73	0.79
I felt more comfortable in social situations than when I am sober.	.77	0.75
Mean (SD)	2.98 (1.03)	2.97 (1.05)
Factor 2		
It was easier to ignore things that were already bothering me.	0.69	0.69

I felt calmer than before getting high.	0.58	0.57
It was easier to distract myself from stressful thoughts.	0.74	0.77
I had fewer worries than before I got high.	0.74	0.74
It was easier for me to have a positive outlook.	0.74	0.69
I felt more content than I normally do.	0.76	0.64
Mean (SD)	3.41 (0.93)	3.89 (0.75)
Factor 3		
I had more energy to stay active.	0.69	0.74
It was easier to focus on the task at hand.	0.77	0.80
It was easier to begin tasks that usually are hard for me to start.	0.81	0.78
I solved a problem I had been struggling with.	0.70	0.74
Tasks I usually find boring I felt excited to do.	0.74	0.65
Mean (SD)	2.63 (0.95)	3.19 (0.91)
Factor 4		
A sexual experience felt more enjoyable than when I am sober.	0.90	0.88
A sexual experience felt more intense.	0.86	0.93
Mean (SD)	2.97 (1.32)	3.39 (1.22)

All factors were correlated (see Table 5) and fit a higher order factor, so I calculated a total score for validation analyses. I examined outcome variable distributions prior to conducting analyses. POSM was normally distributed. Past 30-day marijuana use, past 30-day alcohol use, and PDCQ scores were all overdispersed count variables with outliers, which is appropriate for quasi-Poisson regression. B-MACQ potentially resembled a Poisson distribution; however, it had a significant overdispersion ratio (ratio = 3.62, χ^2 = 3,176.70, p < .001), so I used negative binomial regression for this outcome. Similarly, typical use frequency had a significant overdispersion ratio (ratio = 6.85, χ^2 = 5,770.84, p < .001) and was also modeled with negative binomial regression.

Table 5
Factor Correlation Matrix

	Factor 1	Factor 2	Factor 3	Factor 4
Factor 1	-	.53	.66	.28
Factor 2	.61	-	.53	.29
Factor 3	.59	.56	-	.43
Factor 4	.34	.42	.44	-

Note: College sample correlations are below the diagonal, community sample correlations are above the diagonal. All correlations are significant at $p < .01$.

When testing concurrent validity, POSM significantly predicted past 30-day marijuana use ($b = 0.44$, $SE = 0.04$, $p < .001$, $IRR = 1.56$). The MEEQ-B positive expectancies subscale was a significant predictor of POSM ($b = 0.45$, $SE = 0.03$, $p < .001$; bivariate correlation $r = .43$), supporting convergent validity. POSM significantly predicted MACQ scores ($b = 0.22$, $SE = 0.04$, $p < .001$, $IRR = 1.24$). Discriminant validity analyses revealed that POSM was unrelated to past 30-day alcohol use ($p = .63$). However, POSM was a weak, but significant, predictor of PDCQ ($b = 0.07$, $SE = 0.02$, $p < .001$, $IRR = 1.07$).

Hierarchical quasi-Poisson regression was used to test the influence of adding POSM when predicting past 30-day use (see Table 6 for full regression results). In step one, positive expectancies and negative consequences both positively predicted past 30-day use, while negative expectancies were negatively associated with use. After adding POSM, POSM significantly predicted increased past 30-day use, negative consequences predicted use similar to step 1, and both expectancies were now slightly weaker predictors of use. Pseudo R^2 was unable to be calculated to compare these models.

Next, supplemental analysis using typical use frequency was conducted. POSM positively predicted typical use frequency ($b = 0.51$, $SE = 0.04$, $p < .001$, $IRR = 1.67$). In

Table 6
Hierarchical Quasi-Poisson Regression Predicting Past 30-day Use

	College Sample			Community Sample		
	b	*SE*	*IRR*	*b*	*SE*	*IRR*
Step 1						
Intercept	1.71***	0.20	5.54	3.01***	0.31	20.38
Negative Expectancies	-0.43***	0.04	0.65	-0.22***	0.04	0.80
Positive Expectancies	0.39***	0.04	1.48	0.14*	0.06	1.15
Negative Consequences	0.09***	0.01	1.09	0.03**	0.01	1.03
Step 2						
Intercept	1.35***	0.21	3.87	2.93***	0.31	18.65
Negative Expectancies	-0.37***	0.04	0.69	-0.19***	0.04	0.83
Positive Expectancies	0.29***	0.04	1.34	0.04	0.07	1.05
Negative Consequences	0.08***	0.01	1.09	0.03**	0.01	1.03
Positive Outcomes	0.19***	0.04	1.21	0.12*	0.05	1.13

Note: *p<.05, **p<.01, ***p<.001

hierarchical negative binomial regression step 1, positive expectancies and negative consequences were significant positive predictors of typical use frequency, while negative expectancies negatively predicted use (Veall-Zimmermann pseudo $R^2 = .33$). In step 2, POSM was a positive predictor of typical use frequency, negative consequences predicted use similar to step 1, and expectancies were slightly weaker predictors of use (Veall-Zimmermann pseudo $R^2 = .36$). Change in pseudo R^2 indicated that adding POSM explained 3% more variance in typical use frequency (a small effect; Cohen, 1988), compared to solely using expectancies and negative consequences. See Table 7 for full regression model results.

Table 7
Hierarchical Regression Predicting Typical Use Frequency

	College Sample			Community Sample		
	b	*SE*	*IRR*	*b*	*SE*	*IRR*
Step 1						
Intercept	1.48***	0.19	4.38	2.99***	0.47	19.91
Negative Expectancies	-0.49***	0.04	0.61	-0.31***	0.06	0.74
Positive Expectancies	0.35***	0.04	1.42	0.10	0.09	1.11
Negative Consequences	0.10***	0.01	1.11	0.04**	0.01	1.04
Step 2						
Intercept	0.90***	0.21	2.45	2.85***	0.47	17.30
Negative Expectancies	-0.40***	0.04	0.67	-0.26***	0.07	0.77

Positive Expectancies	0.23***	0.04	1.25	-0.02	0.11	0.98
Negative Consequences	0.10***	0.01	1.10	0.04**	0.01	1.04
Positive Outcomes	0.27***	0.04	1.31	0.17*	0.07	1.18

Note: *p<.05, **p<.01, ***p<.001. College sample data modeled as a negative binomial regression, pseudo R^2 change = .03. Community sample data modeled as a quasi-Poisson regression.

STUDY 2

Method

Participants and Procedure

Adults (at least 21 years old) from the United Stated (nationally recruited) who reported past-month marijuana use were invited to complete the same survey as used in Study 1. Participants were recruited from previous marijuana research (Prince et al., 2018), Facebook posts, and snowball recruiting. Data were collected from January to April 2021. N = 216 participants completed the survey; however, one person was removed for inattentive responding and one person was removed for missing more than 50% of the POSM items. The analytic sample included N = 214 participants, who were an average age of 35.73 years old (SD = 8.92, range 22.80-69.66), 45.3% female, were 90.7% White, and 92.1% non-Hispanic. Data were collected via online computerized surveys that participants completed on their own devices. Participants received a $10 Amazon Gift Card in exchange for study participation. The study was approved by the university institutional review board and all participants consented to participation.

Measures

The study battery included the same measures as included in Study 1. This included demographics, past 30-day marijuana and alcohol use, typical marijuana use frequency, MEEQ-B (positive $\alpha = .45$, negative $\alpha = .51$ in this sample), B-MACQ ($\alpha = .79$ in this sample), PDCQ ($\alpha = .91$ in this sample), and POSM. While the original MEEQ was designed for use in adult samples and is one of the most common marijuana expectancy scales, the MEEQ-B was validated within adolescent samples (Torrealday et al., 2008). The MEEQ-B has not typically been used in adult samples, and therefore, it is unknown well how this subset of MEEQ items measures marijuana expectancies in adult populations. I maintained the MEEQ-B in this study because few studies have examined marijuana expectancies among adults, and the original MEEQ items were validated in adult samples, suggesting these items may still be significant indicators of marijuana expectancies. The POSM included in this study was limited to the 29 items from the final CFA from Study 1.

Analysis

Initially, I examined response patterns for item frequency, valence, and influence. I removed items with limited endorsement ranges, a mean of "negative" or "slightly negative" valence, or a mean of "not at all influential" or "slightly influential." Next, I calculated item-level correlations for remaining scale items. Items that had mixed positive and negative correlations or mostly negative correlations with other items or the total score were removed. Lastly, I examined missingness to ensure items were missing less than 5% of data, and participants missing more than 50% of item data were removed.

CFA initially replicated the final model from Study 1 CFA. MLR estimation accounted for violations of multivariate normality. I determined excellent model fit based on a non-significant chi-square, CFI > .94 (> .90 is adequate), and RMSEA < .05 (RMSEA < .08 for adequate fit). I considered models to have good fit with a significant chi-square if other fit indicators were met expected criteria. To improve model fit and factor loadings, I removed poorly loading items (<.40) and then conducted CFA with remaining scale items. Modification indices identified potential redundant items, particularly among factors with notably more items than other factors (DeVellis, 2012; Muthén & Muthén, 2020). I determined the final items by establishing excellent model fit and all items having acceptable standardized factor loadings.

Next, I calculated ω was used to measure internal reliability (ω > .70 acceptable, ω .80 to .95 great, ω > .95 indicating a need for further consolidation). Lastly, supplemental CFA determined if a higher order factor was present within the POSM.

Once the scale was finalized through CFA, I conducted invariance testing to compare the scale's psychometric properties between the college and community samples (Millsap, 2011). I examined configural, metric, scalar, and strict factorial invariance sequentially, as each subsequent invariance test relies on the previous test being upheld. Configural invariance refers to the scale having the same factor structure, while allowing factor loadings, intercepts, and residuals to be freely estimated (Meredith, 1993; Muthén & Muthén, 2020). Metric invariance indicates items have the same factor loadings across groups. This was tested by constraining factor loadings, while still allowing intercepts and residual variance to be freely estimated. Scalar invariance tests determine if intercepts were consistent across groups. This was tested by constraining factor structure, factor loadings, and intercepts across groups. Lastly, strict factorial invariance constrains all previously constrained parameters and residual variance to determine if residuals are invariant across groups (Meredith, 1993). Each successive form of measurement invariance establishes greater scale equivalency between populations, thus supporting greater comparability of scale results. If strict factorial invariance is established, then the measurement model can be considered equivalent across samples (Millsap, 2011). If strict factorial invariance is not established, the scale can still be useful in different populations; however, results between these populations cannot be directly compared.

When testing model invariance, I conducted multigroup confirmatory factor analysis with factor variances fixed to one and factor loadings allowed to be freely estimated (Muthén & Muthén, 2020). Chi-square difference tests were computed to compare models for each level of invariance (e.g., configural versus metric; Xu & Tracey, 2017). Non-significant chi-square statistics comparing two levels of invariance indicated that the model is invariant at the higher level of invariance testing. Since chi-square is substantially influenced by sample size, configural invariance could also be established by examining the RMSEA and CFI, using the previously established model fit cutoff criteria (Hu & Bentler, 1999). I evaluated metric, scalar, and strict factorial invariance by examining the model chi-square comparison tests (Muthén & Muthén, 2020). I continued to use MLR estimation when conducting invariance testing.

Following invariance testing, I conducted scale validation analyses and hypothesis testing. To test concurrent validity, POSM predicted past 30-day use. I examined convergent validity by using positive expectancies to predict POSM, as well as POSM scores to predict negative outcomes of use. To establish discriminant validity, POSM predicted past 30-day alcohol use, then POSM predicted PDCQ. Finally, I used hierarchical regression to examine incremental validity by initially regressing past 30-day use on MEEQ-B subscales and B-MACQ scores (step 1), then adding the POSM (step 2) to examine change in variance. I conducted supplemental analyses using typical use frequency in place of past 30-day use to examine a more nuanced measure of use frequency.

Results

Means and standard deviations for all study variables are presented in Table 2. Examining distributions of POSM item frequency, valence, and influence resulted in six items being removed. Item-level and item-total correlations were calculated for the 23 remaining items. All item correlations were positive, so all items were maintained. Missing data in these items ranged from 0% to 1.4%, which is considered ignorable and missing at random.

The first CFA was conducted with the 23 POSM items. The resulting model fit ranged from adequate to poor, $\chi^2 = 467.39$, df = 224, p < .001, CFI = .88, RMSEA = .071 (90% CI .062-.080). Standardized factor loadings ranged from .30 to .92. Two items with factor loadings below .40 were removed and a subsequent CFA was conducted on the remaining twenty-one items. The second CFA had marginally improved fit, $\chi^2 = 374.53$, df = 183, p < .001, CFI = .90, RMSEA = .070 (90% CI .060-.080), and standardized factor loadings between .47 and .93. The item with the lowest standardized factor loading (.47) was the only item below .50 and was removed. I reviewed modification indices for potentially redundant items, particularly on factors with a disproportionate number of items. Ultimately, I removed four items, leaving 17 items for the subsequent CFA.

The final CFA achieved excellent fit, $\chi^2 = 178.49$, df = 113, p < .001, CFI = .96, RMSEA = .052 (90% CI .037-.066). Standardized factor loadings ranged from .57 to .92 (see Table 4). All four factors demonstrated excellent reliability, factor 1 $\omega = .86$, factor 2 $\omega = .84$, factor 3 $\omega = .86$, and factor 4 $\omega = .90$. Supplemental analysis supported the presence of a higher order factor, as demonstrated by adequate model fit, $\chi^2 = 182.93$, df = 115, p < .001, CFI = .95, RMSEA = .053 (90% CI .038-.066). All scale factors significantly loaded onto the higher order factors (standardized factor loadings: 0.83, 0.71, 0.92, 0.47, respectively).

Measurement invariance testing supported configural invariance (i.e., factor structure) between samples, as demonstrated by excellent model fit in the configural model, $\chi^2 = 420.83$, df = 266, p < .001, CFI = .97, RMSEA = .040 (90% CI .034-.045). There was a significant chi-square difference test when comparing configural model to the metric model, $\chi^2 = 30.14$, df = 13, p = <.01. Since there were observed differences between these models, metric invariance was not supported. Results suggested that the scale has the same factor structure in each sample, however subscale items contribute a different amount of variance to each factor between the samples When examining item intercepts in the metric models, the only item with a notably higher intercept in the college sample was “I talked to someone new in a situation where I usually would have kept to myself.” The intercepts for the other three Social Enhancement items were fairly equivalent between samples. The remaining items all had higher intercepts in the community sample. Since metric invariance was not established, scalar and strict factorial invariance were not examined.

All factors were correlated (see Table 5) and fit a higher order factor, so a total scale score was calculated. Distributions for outcome variables were examined prior to conducting validity analyses. POSM was normally distributed. Past 30-day marijuana use, past 30-day alcohol use, MACQ scores, PDCQ scores, and typical use frequency were overdispersed count variables with outliers, so they were modeled using quasi-Poisson regression.

Concurrent validity analysis revealed that POSM positively predicted past 30-day marijuana use ($b = 0.19$, $SE = 0.04$, $p < .001$, $IRR = 1.21$). Convergent validity analyses revealed that positive expectancies were a significant predictor of POSM ($b = 0.86$, $SE = 0.09$, $p < 001$; bivariate correlation $r = .56$). However, POSM did not predict negative consequences ($p = .27$). When testing discriminant validity analyses, POSM negatively predicted past 30-day alcohol use ($b = -0.29$, $SE = .10$, $p < .01$, $IRR = 0.75$). POSM was unrelated to the PDCQ ($p = .34$).

Hierarchical quasi-Poisson regression tested the influence of POSM when predicting past 30-day marijuana use frequency (see Table 6 for full regression results). In step one, positive expectancies and negative consequences related to greater use, while negative expectancies negatively predicted use. In step 2, POSM and negative consequences positively predicted use, negative expectancies negatively predicted use, and positive expectancies were no longer a significant predictor of use. Pseudo R^2 was unavailable to compare these models, so the unique variance accounted for by POSM could not be calculated.

Supplemental analyses evaluated typical use frequency. POSM remained a positive predictor of use frequency ($b = 0.25$, $SE = 0.06$, $p < .001$, $IRR = 1.28$). In hierarchical quasi-Poisson regression step 1, negative consequences related to greater use, negative expectancies was a negative predictor of use, and positive expectancies did not predict typical use frequency. In step 2, POSM and negative consequences were significant positive predictors of typical use frequency, while negative expectancies remained a negative predictor, and positive expectancies were nonsignificant. Pseudo R^2 was unavailable to compare change in model variance from step 1 to 2. See Table 7 for full regression model results.

DISCUSSION

The present study described the development, psychometric evaluation, and validation of the first marijuana use-related positive outcomes measure. Factor analyses supported there were four related factors present within the scale items related to social, mood and relaxation, perceptual, and sexual positive outcomes. Additionally, configural invariance established between the samples indicated the factor structure was the same in each sample; however, the factor loadings, intercepts, and residual variances varied across the college and adult community samples. Since the factor structure was upheld in both samples and demonstrated excellent fit, I recommend that the same scale items, subscales, and mean scoring are used in college and community samples; however, scores in different populations should not be directly compared.

Study results largely upheld the predicted hypotheses. Positive outcomes were related to recent marijuana use (concurrent validity) and positive expectancies (convergent validity) in both samples. Positive outcomes and negative consequences (convergent validity) were only related in the college sample. Discriminant validity analyses supported that positive outcomes were unrelated to recent alcohol use among college students, and negatively related to alcohol use in the community sample. Conversely, there was a small relation with positive drinking outcomes in the college sample, and no relation in the community sample. Incremental validity analysis noted that positive outcomes had a small but significant increase in explained variance when predicting typical use frequency. Addition of positive outcomes in all hierarchical regressions explained a significant amount of variance in use frequency. Notably, regression analyses in both samples supported that positive outcomes are unique from positive expectancies and hold importance for recent use.

Factor Structure

The observed factors within the positive outcomes construct were similar to factors identified among marijuana expectancies and motives scales, as well as the alcohol positive outcomes scale (Aarons et al., 2001; W. R. Corbin et al., 2008; Jordan et al., 2019; Simons et al., 1998). Several of the marijuana expectancy factors (Aarons et al., 2001) correspond with identified positive outcomes factors, including Relaxation and Tension Reduction (Mood Enhancement and Relaxation), Social and Sexual Facilitation (Social Enhancement, Sexual Enhancement), and Perceptual and Cognitive Enhancement (Perceptual Enhancement). Expectancy factors that did not correspond related to negative expectancies (e.g., Craving and Physical Effects), and thus should be unique from positive outcomes.

Positive outcome factors also related to identified motives for use factors including enhancement, expansion, coping, and social motives (from the Marijuana Motive Questionnaire (MMQ); Simons et al., 1998). Factors were most associated with expansion (e.g., feeling more creative; Perceptual Enhancement), social (e.g., improves social gatherings; Social Enhancement), and coping (e.g., forget my worries; Mood Enhancement and Relaxation) motives. Enhancement motives (e.g., liking the feeling) were related to items removed during EFA and CFA (e.g., "I enjoyed the feeling of being high"). Initial items related to enhancement motives were heavily endorsed with limited variability, and thus explained less variance in the overarching positive outcomes construct. Given their restricted endorsement ranges, they were removed. In turn, while these may be positive outcomes related to use, their limited variability made them less useful in differentiating across different levels of the positive outcomes construct.

Positive marijuana and alcohol outcomes had notable similarity in factor structure (Jordan et al., 2019). Three of the four alcohol positive outcome factors (i.e., Sociability, Tension Reduction, Sexual Enhancement) corresponded with marijuana positive outcome factors (i.e., Social Enhancement, Mood Enhancement and Relaxation, Sexual Enhancement). The final alcohol factor, Liquid Courage, had some items similar to the Perceptual Enhancement factor (e.g., changes in problem-solving skills). However, Liquid Courage also encompassed disinhibiting effects of alcohol that increase social boldness, and may be less prominent with marijuana use (Higgins & Stitzer, 1986; Stoner et al., 2007). Additionally, positive marijuana and alcohol factors both loaded onto a higher-order factor, indicating an overarching positive outcomes construct encompasses experienced positive outcomes.

The positive outcome factors had medium to large correlations in both samples (Cohen, 1988). This supported that as individuals experience greater positive outcomes of use, increases are likely to occur in several domains. This may be particularly noted among individuals who use the most frequently (e.g., those with dependence), as they may be more likely to globally perceive positive aspects of use (Linkovich-Kyle & Dunn, 2001). While associations were weakest with the Sexual Enhancement factor, albeit still moderate, this may partially be due to having a two-item factor. It may also relate to sexual behavior occurring in limited contexts and often involving another willing participant (Cooper et al., 2000), which may be less available relative to other positive experiences.

Scale Validity and Study Outcomes

When examining concurrent validity, positive outcomes related to recent use as hypothesized. In the college sample, a one-unit increase in average positive outcome frequency (e.g., an average increase from "sometimes" to "often") was related to a 21% increase in past 30-

day use and 31% increase in typical use frequency, when controlling for expectancies and negative consequences. In the community sample, a one-unit increase in average positive outcome frequency was associated with a 13% increase in past 30-day use and an 18% increase in typical use frequency. These findings are consistent with operant conditioning, as individuals who experience greater reinforcement are likely to use more often, which influences likelihood of dependence (Budney et al., 2007; Ferster & Skinner, 2014). Additionally, positive outcomes were more influential than negative outcomes in predicting recent use in both samples. This is also supported by previous research suggesting that individuals likely use for the reinforcing effects and, particularly among those with dependence, may discount experienced negative consequences (Boden et al., 2013; Buckner et al., 2013; Connor et al., 2011; Lee et al., 2010; Linkovich-Kyle & Dunn, 2001).

Also consistent with study hypotheses, positive expectancies directly predicted positive outcomes. This is supported by social learning theory, as expectancies are informed by experienced outcomes and influence future outcomes (Maisto et al., 1999; Metrik et al., 2009). Importantly, the two variables were not collinear, indicating that they are related, but distinct constructs. This was further underscored by their unique, significant prediction of recent use. Among community adults, positive expectancies were no longer a significant predictor of past 30-day use after adding positive outcomes to the model. Furthermore, positive expectancies were unrelated to typical use frequency among community adults, while positive outcomes were significantly related. This suggests there is shared variance between these constructs; however, the outcomes adults actually experience may better explain recent use than the outcomes they expect to occur.

Positive outcomes also related to negative consequences in the college sample, as predicted. This may be explained by positive outcomes reinforcing continued use, and frequent or continued use portending risk for increased negative consequences (Pearson, 2019). Interestingly, positive outcomes were unassociated with negative consequences among community adults. One explanation for this might be that there could be greater variability in lifetime duration of use and dependence among adults. Operant conditioning suggests that over time, individuals may learn to alter their behaviors to mitigate negative consequences (Reynolds, 1975). Adults with longer use histories may have refined their use to maintain positive outcomes, while minimizing negative consequences. Other adults may have less experience and still experience a mix of positive and negative consequences. And lastly, there may be adults who are dependent, perceive notable positive outcomes, and devalue possible negative consequences (Kilmer et al., 2007; Linkovich-Kyle & Dunn, 2001), thus underreporting their occurrence.

When examining alcohol use, positive marijuana outcomes were unrelated to recent alcohol use and weakly associated with positive drinking outcomes in the college sample. As expected, students' alcohol use did not vary as a function of how positively they perceive marijuana outcomes. Past research has noted that college students may substitute marijuana and alcohol use at times, and use concurrently at other times, (O'Hara et al., 2016; Subbaraman, 2016), implicating a separate decision making process for each substance. Moreover, since use of these substances is illegal for underage students, use may be affected by context, availability, and punitive responses. Therefore, external factors may also dictate a student's ability to use each substance, independently of how positively they perceive outcomes of marijuana use. Regarding the weak association with alcohol outcomes, there is some overlap in marijuana and alcohol outcome factors, as well as subjective effects (Earleywine, 2005; Jordan et al., 2019; Sher &

Wood, 2005). In turn, college students who perceive reinforcement from similar aspects of these drugs (e.g., relaxation), may use the more available substance to achieve this effect.

Among community adults, positive marijuana outcomes were negatively associated with recent alcohol use and unrelated to positive alcohol outcomes. In this study, a one-unit increase in positive outcomes was associated with a 25% reduction in past 30-day alcohol use. For adults, marijuana use is legal in many states, and in states where it is illegal, adults are more likely than students to have a private residence where they can use without punitive repercussions. In turn, adults who experience greater positive marijuana outcomes may choose to use marijuana instead of alcohol. Congruently, some adults have reported substituting marijuana for alcohol, citing preferable outcomes (Lucas et al., 2013; Reiman, 2009). Similarly, longitudinal research suggested that reducing marijuana penalties was associated with decreased alcohol use among individuals most likely to use marijuana (Subbaraman, 2016). Since adults may have greater ability to use their preferred substance, they may differentiate more between their perceived positive outcomes of each drug. In both samples, the differentiation of positive outcomes from alcohol use and outcomes is supportive of discriminant validity.

Study Implications

Several implications can be drawn from the study findings. Foremost, positive outcomes play an important role in understanding marijuana use frequency. As expected, those who use at the highest rates also report the highest level of positive outcomes, as well as negative consequences. In turn, positive outcomes likely serve as a notable reinforcing factor and target for interventions looking to reduce negative consequences and dependence. While expectancy and motives measures may help identify similar intervention targets, they are limited to explaining one's motivation for use and what they expect to experience. Measuring positive outcomes may better inform how strongly outcomes are reinforcing use (either by facet or in general). In turn, interventions can match the degree of reinforcement (e.g., less frequent, lower valence positive outcomes may fit briefer interventions).

Additionally, several of the identified positive outcomes (e.g., relaxation, reduced worrying) can also be achieved through healthier means. This may be particularly important, as individuals using marijuana to cope with mental distress (e.g., worrying) experience higher rates of negative consequences and dependence (Bonn-Miller, Vujanovic, et al., 2008; Bonn-Miller, Zvolensky, et al., 2008; Johnson et al., 2010). Clinicians working with individuals who endorse Mood Enhancement and Relaxation outcomes could provide relaxation techniques (Manzoni et al., 2008), mindfulness practices (Lancaster et al., 2016), or evidence-based interventions for stress reduction and anxiety (e.g., mindfulness-based stress reduction, cognitive behavioral therapy (CBT); Grossman et al., 2004; Hofmann & Smits, 2008). These strategies may teach more efficacious, long-term skills that could offset marijuana use and reduce associated negative consequences.

Similarly, individuals endorsing Social Enhancements may be using marijuana to reduce social anxiety or compensate for social deficits (Buckner et al., 2007). Using marijuana to cope with these concerns may further social and emotional avoidance. Conversely, providing interventions to effectively cope (e.g., CBT) may produce lasting social benefits, thus reducing the need for marijuana in these situations. As alternative strategies are practiced and become reinforced, continued positive outcomes measurements may help gauge if new strategies are offsetting marijuana's reinforcement.

Understanding positive outcomes can also help enhance motivational interviewing (MI) techniques that are commonly embedded in marijuana dependence treatment (DiClemente et al., 2017; W. R. Miller & Rollnick, 2012; Smedslund et al., 2011; Walker et al., 2006, 2011). MI is based on developing discrepancies, exploring ambivalence, and building motivation for change. One target for building discrepancy identified in this study is the distinction between positive expectancies and positive outcomes. Since these constructs were related but not collinear, individuals may expect a positive outcome that does not actually occur. Exploring discrepancies between one's expectations and experienced outcomes may help an individual identify distorted perspectives, which can motivate behavioral change (Markland et al., 2005). For example, an individual may endorse expecting social benefits from use, however, report few experienced social outcomes. Highlighting this inconsistency and challenging their expectation can provide a more balanced, accurate perception of use outcomes. Since individuals often want to act consistently with their values and beliefs (Markland et al., 2005), exposing inconsistencies can often motivate behavioral change. Continuing the previous example, if the individual holds a value of wanting positive socialization, noting that using marijuana does not achieve this goal (or possibly even detracts) may motivated reductions or abstinence from use in social circumstances.

Study results also suggested that among a sample of frequently using community adults, there was no association between reported positive and negative marijuana outcomes. While this is possible, it may also reflect mental biases commonly associated dependence that emphasize positive outcomes and filter out negative aspects of marijuana use. Underreporting of negative consequences may also relate to defensiveness around one's substance use (Feldstein & Miller, 2007). MI and similar therapeutic interventions could leverage the current study's finding by providing a nonjudgmental space for individuals with high levels of reported positive outcomes to explore potential negative consequences of use and develop a balanced view of their use-related outcomes. Identifying negative consequences of use is often an important component in motivating behavior change and informing salient harm reduction approaches. Alternatively, some individuals may experience heightened positive outcomes without concomitant negative consequences. If so, harm reduction and psychoeducational approaches may help these individuals identify warning signs should their use become problematic or escalations in negative consequences.

Strengths and Limitations

The present study had several notable strengths. The large college sample allowed for more stable estimations of factor structure. Additionally, college-aged young adults (i.e., 18-24 years old) report particularly high use (Center for Behavioral Health Statistics and Quality, 2019) and rates of dependence (Farmer et al., 2015). The present study provides additional insight into measurement and risk factors for this group. Similarly, the nationally recruited sample of adults may be particularly important to study while recreational legalization becomes more common, as these are the individuals who will gain increased access to marijuana use. Accurately measuring and understanding how use is reinforced in this population can best inform harm reduction policies and interventions. The nationally recruited sample, which contained a notable age range and diverse sexual orientations, also suggestions broader generalization of study findings. Another strength was that the POSM was developed from qualitative input from marijuana-using participants (inductive) and previous marijuana literature (deductive), rather than only using one of these approaches or adapting an existing alcohol scale. This approach is considered the ideal strategy for item generation (DeVellis, 2012). While many marijuana scales are adapted from alcohol measures (e.g., MACQ, MMQ), doing so may overlook important facets unique to marijuana use.

While there were several strengths, this study should also be interpreted considering its limitations. Data were collected during the Covid-19 pandemic, which was associated with changes in substance use behaviors (Ornell et al., 2020; Rogers et al., 2020). Additionally, limited social contact during the pandemic may have altered participant responses to socially-based scale items. Therefore, results from this study may be different from behavior prior to and after the pandemic. Additionally, the surveys in this study are cross-sectional, which lack temporal sequencing, so causal claims cannot be made based on study findings. There was also limited ethnic and racial diversity among the study participants, particularly in the community sample. Findings should be tested among more diverse samples prior to generalizing results. While the MEEQ-B subscales demonstrated similar reliability to the scale development study, negative expectancies in both samples and positive expectancies in the community sample were considered to have poor overall reliability. Therefore, there may be notable error in these measurements which limits how accurately subscale items may be measuring a shared construct.

Future Research and Conclusion

Future research should continue to examine how marijuana-related positive outcomes serve to reinforce use over time. Implementing longitudinal designs could determine how experienced positive outcomes naturally change as use escalates and is maintained. This may be particularly important in determining if certain observed changes in positive outcomes are related to development of dependence. Longitudinal studies examining positive outcomes among adolescents and individuals who recently initiated use may best elucidate these trends. Longitudinal designs could also test social learning theory within marijuana use to determine how individual’s behavior is shaped by their previously experienced outcomes, social influences, and cognitions (e.g., expectancies). Similarly, fine-grained measurement of positive outcomes using ecological momentary assessment may also reduce recall biases and better distinguish between expected and experienced outcomes. Further differentiating these constructs may continue to inform harm reduction approaches and clinical interventions. Research should also determine if positive outcomes vary by population (e.g., biological sex, racial minorities) and other individual differences (e.g., impulsivity, sensation seeking).

Positive outcomes are a central aspect of marijuana use. While several clinical approaches incorporate positive outcomes into treatment, marijuana research has only started to examine their role in maintained use. Developing and validating a positive outcomes measure is one important step toward more comprehensively studying and understanding marijuana use. As recreational marijuana use becomes more prevalent, it is vital to build stronger literature on factors contributing to problematic use and dependence. Doing so may best inform harm reduction policies and interventions, mitigating the potential harms of increased access to marijuana.

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APPENDIX A: DEMOGRAPHIC INFORMATION

1. What is your date of birth? (Responses must be entered as MM/DD/YYYY) ________

2. What was the sex assigned to you at birth?
    a. Male
    b. Female
    c. Intersex
    d. Another ________
    e. Do not wish to respond

3. What is your race? (Choose all that apply)
    a. American Indian or Alaska Native
    b. Asian
    c. Black or African American
    d. Native Hawaiian or Other Pacific Islander
    e. White
    f. Do not wish to respond

4. What is your ethnicity? (Choose one)
    a. Hispanic or Latino
    b. Not Hispanic or Latino
    c. Do not wish to respond

5. What is your sexual orientation? ________

6. Choose a number that best describes your sexual orientation/preference:
    a. Exclusively homosexual (1)
    b. 2
    c. 3
    d. Bisexual (4)
    e. 5
    f. 6
    g. Exclusively heterosexual (7)
    h. Asexual
    i. Pansexual
    j. Do not wish to respond

7. How do you define your Gender Identity?
    Note that Cisgender terms Cis Man and Cis Woman denote individuals whose sense of gender identity corresponds with the sex assigned to them at birth.
    (We are attempting to better understand relations between gender identity and behavior)
    {Choose all that apply}
    a. Agender

b. Androgynous
c. Cis Man
d. Cis Woman
e. Demiboy
f. Demigirl
g. Gender Fluid
h. Gender Non-Binary
i. Gender Non-Conforming
j. Gender Fluid
k. Gender Non-Binary
l. Gender Non-Conforming
m. Genderless
n. Genderqueer
o. Man
p. Third Gender
q. Trans Man
r. Trans Woman
s. Transgender
t. Transperson
u. Two Spirit
v. Woman
w. Other ________
x. Choose not to respond

APPENDIX B: MARIJUANA AND ALCOHOL USE

1. In the past 30 days, on how many days did you consume marijuana in any form? (e.g., smoked, edible, vaporized, concentrate). Please respond 0-30. ________

2. In the past 30 days, on how many days did you consume alcohol? Please respond 0-30. ________

3. During a week of typical marijuana use in the past 3 months, please indicate times and days that you used marijuana.

	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday
12am-4am						
4am-8am						
8am-12pm						
12pm-4pm						
4pm-8pm						

APPENDIX C: POSITIVE OUTCOMES SCALE FOR MARIJUANA

Think about the outcomes you have experienced when using marijuana in the past month. When responding to each item, please respond with:

- How often the outcome has actually occurred for you after using marijuana in the past month.
- Rating how positive or negative the outcome typically was for you.
- Rating how likely it is that the outcome will influence your future marijuana use.

After using marijuana…

1. It felt easier than normal to be open with others.
2. I had more energy to stay active.
3. It was easier to ignore things that were already bothering me.
4. I felt calmer than before getting high.
5. It was easier for me to make conversation when I usually would have talked less.
6. A sexual experience felt more enjoyable than when I am sober.
7. It was easier to begin tasks that usually are hard for me to start.
8. I talked to someone new in a situation where I usually would have kept to myself.
9. It was easier to distract myself from stressful thoughts.
10. I had fewer worries than before I got high.
11. It was easier to focus on the task at hand.
12. A sexual experience felt more intense.
13. I solved a problem I had been struggling with.
14. I felt more comfortable in social situations than when I am sober.
15. It was easier for me to have a positive outlook.
16. Tasks I usually find boring I felt excited to do.
17. I felt more content than I normally do.

<u>Response scales:</u>
How often: 1 = *Never*, 2 = *Rarely*, 3= *Sometimes*, 4 = *Often*, 5 = *Always/Almost Always*
Valence: 1 = *Negative*, 2 = *Slightly Negative*, 3 = *Neutral*, 4 = *Slightly Positive*, 5 = *Positive*
Influence on future use: 1 = *Not at All Influential*, 2 = *Slightly Influential*, 3 = *Somewhat Influential*, 4 = *Influential*, 5 = *Highly Influential*
*Note: the frequency response scale is the primary scale. Other scales are optional supplementary scales. Scale instructions should be adjusted to fit the administered scales.

<u>Scoring:</u>
A total score is calculated by taking a mean of all items. Subscale scores are calculated by taking a mean of the following items:

- Social Enhancement: 1, 5, 8, 14
- Mood Enhancement and Relaxation: 3, 4, 9, 10, 15, 17
- Perceptual Enhancement: 2, 7, 11, 13, 16
- Sexual Enhancement: 6, 18

APPENDIX D: MARIJUANA EFFECT EXPECTANCY QUESTIONNAIRE – BRIEF

Answer according to how much you agree or disagree with each statement.

1. Marijuana makes it harder to think and do things (harder to concentrate or understand; slows you down when you move).
   1 = *Disagree Strongly* to 5 = *Agree Strongly*

2. Marijuana helps a person relax and feel less tense (helps you unwind and feel calm).
   1 = *Disagree Strongly* to 5 = *Agree Strongly*

3. Marijuana helps people get along better with others and it can help you feel more sexual (talk more; feel more romantic).
   1 = *Disagree Strongly* to 5 = *Agree Strongly*

4. Marijuana makes a person feel more creative and perceive things differently (music sounds different; things seem more interesting).
   1 = *Disagree Strongly* to 5 = *Agree Strongly*

5. Marijuana generally has bad effects on a person (you become angry or careless; after feeling high you feel down).
   1 = *Disagree Strongly* to 5 = *Agree Strongly*

6. Marijuana has effects on a person's body and gives a person cravings (get the munchies/hungry; have a dry mouth; hard to stop laughing).
   1 = *Disagree Strongly* to 5 = *Agree Strongly*

APPENDIX E: BRIEF MARIJUANA CONSEQUENCES QUESTIONNAIRE

The following is a list of things that sometimes happen to people either during, or after they have been using marijuana. Select either YES or NO to indicate whether that item describes something that has happened to you in the past month.

1. I have driven a car when I was high.
   0 = *No*, 1 = *Yes*

2. I have felt in a fog, sluggish, tired, or dazed the morning after using marijuana.
   0 = *No*, 1 = *Yes*

3. I have had less energy or felt tired because of my marijuana use.
   0 = *No*, 1 = *Yes*

4. I have been less physically active because of my marijuana use.
   0 = *No*, 1 = *Yes*

5. I have lost motivation to do things because of my marijuana use.
   0 = *No*, 1 = *Yes*

6. I often have thought about needing to cut down or to stop using marijuana.
   0 = *No*, 1 = *Yes*

7. I have spent too much time using marijuana.
   0 = *No*, 1 = *Yes*

8. I haven't been as sharp mentally because of my marijuana use.
   0 = *No*, 1 = *Yes*

9. I have felt like I needed a hit of marijuana after I'd gotten up (that is, before breakfast).
   0 = *No*, 1 = *Yes*

10. I have tried to quit using marijuana because I thought I was using too much.
    0 = *No*, 1 = *Yes*

11. I have had trouble sleeping after stopping or cutting down on marijuana use.
    0 = *No*, 1 = *Yes*

12. I have awakened the day after using marijuana and found I could not remember a part of the evening before.
    0 = *No*, 1 = *Yes*

13. I have felt anxious, irritable, lost my appetite or had stomach pains after stopping or cutting down on marijuana use.
    0 = *No*, 1 = *Yes*

14. I have neglected obligations to family, work, or school because of my marijuana use.
    0 = *No*, 1 = *Yes*

15. When using marijuana I have done impulsive things that I regretted later.
    0 = *No*, 1 = *Yes*

16. I have been unhappy because of my marijuana use.
    0 = *No*, 1 = *Yes*

17. I have received a lower grade on an exam or paper than I ordinarily would have because of marijuana use.
    0 = *No*, 1 = *Yes*

18. The quality of my work or schoolwork has suffered because of my marijuana use.
    0 = *No*, 1 = *Yes*

19. I have been overweight because of my marijuana use.
    0 = *No*, 1 = *Yes*

20. I have become very rude, obnoxious, or insulting after using marijuana.
    0 = *No*, 1 = *Yes*

21. I have gotten into physical fights because of my marijuana use.
    0 = *No*, 1 = *Yes*

APPENDIX F: POSITIVE DRINKING CONSEQUENCES QUESTIONNAIRE

Please indicate the number of times you have experienced each of the following consequences of drinking in the past month. Please do not report experiencing consequences simply because you believe that they ordinarily occur when you drink. Think about actual drinking occasions and report the consequences experienced on these occasions.

1. I approached a person that I probably wouldn't have spoken to otherwise.
   1 = *0*, 2 = *2-3*, 3 = *3-5*, 4 = *6-10*, 5 = *>10*

2. I told a funny story or joke and made others laugh.
   1 = *0*, 2 = *2-3*, 3 = *3-5*, 4 = *6-10*, 5 = *>10*

3. I revealed a personal feeling or emotion that I had previously kept secret.
   1 = *0*, 2 = *2-3*, 3 = *3-5*, 4 = *6-10*, 5 = *>10*

4. I felt like I had enough energy to stay out all night partying or dancing.
   1 = *0*, 2 = *2-3*, 3 = *3-5*, 4 = *6-10*, 5 = *>10*

5. In a situation in which I would usually have stayed quiet, I found it easy to make conversation.
   1 = *0*, 2 = *2-3*, 3 = *3-5*, 4 = *6-10*, 5 = *>10*

6. I stood up for a friend or confronted someone who was in the wrong.
   1 = *0*, 2 = *2-3*, 3 = *3-5*, 4 = *6-10*, 5 = *>10*

7. I found myself in a frightening situation and I felt surprisingly fearless.
   1 = *0*, 2 = *2-3*, 3 = *3-5*, 4 = *6-10*, 5 = *>10*

8. I found a creative solution to a problem I might otherwise have had difficulty solving.
   1 = *0*, 2 = *2-3*, 3 = *3-5*, 4 = *6-10*, 5 = *>10*

9. I felt especially confident that other people found me attractive.
   1 = *0*, 2 = *2-3*, 3 = *3-5*, 4 = *6-10*, 5 = *>10*

10. The intensity of a sexual experience was enhanced.
    1 = *0*, 2 = *2-3*, 3 = *3-5*, 4 = *6-10*, 5 = *>10*

11. I acted out a sexual fantasy that I might ordinarily be embarrassed to reveal or attempt.
    1 = *0*, 2 = *2-3*, 3 = *3-5*, 4 = *6-10*, 5 = *>10*

12. On a particularly stressful day, I noticed a release of tension from my muscles and nerves.

1 = *0*, 2 = *2-3*, 3 = *3-5*, 4 = *6-10*, 5 = *>10*

13. Something that would have ordinarily made me upset or emotional didn't really get me down.
    1 = *0*, 2 = *2-3*, 3 = *3-5*, 4 = *6-10*, 5 = *>10*

14. Things that I had been worrying about all day no longer seemed important.
    1 = *0*, 2 = *2-3*, 3 = *3-5*, 4 = *6-10*, 5 = *>10*