Identifying High-Impact Cannabis Protective Behavioral Strategies Using Machine Learning

CENTER ON ALCOHOL, SUBSTANCE USE & ADDICTIONS

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INTRODUCTION

- Research has consistently identified Cannabis **Protective Behavioral Strategies (PBS)** as robust protective factors associated with lower levels of cannabis-related harms (Bravo et al., 2017)
- However, most of the existing literature focuses on aggregate data, such as total scores or subscales of the **Protective Behavioral Strategies for Marijuana (PBSM)** scale
- This approach may obscure the unique predictive utility of individual behaviors
- The present study aimed to bridge this gap by identifying which specific cannabis PBS items are the strongest predictors of cannabis-related outcomes

METHOD

PARTICIPANTS

- College students were recruited from one of 10 universities across three consecutive years of data collection by the Addictions Research Team
- Our analytic samples were restricted to past 30-day cannabis users (ART2 N = 1,200; ART3 N = 1,308; ART4 N = 607)

MEASURES

- Cannabis PBS were assessed using the 17-item PBSM (Pedersen et al., 2017)
- Cannabis use frequency was assessed as # of days used in the past 30 days (**MJ30**)
- Negative cannabis-related consequences were assessed using the brief 21-item version of the Marijuana Consequences Questionnaire (MACQ; Simons et al., 2012)
- CUD symptoms were assessed by the 8-item Cannabis Use Disorder Identification Test-Revised (CUDIT-R; Adamson et al., 2010)

ANALYSIS PLAN

- We utilized two machine learning approaches: random forest and elastic net regression
- Each of these techniques allow for the identification of the most influential variables within a large dataset while accounting for multicollinearity

RESULTS

Table 1. Regression Coefficients from Elastic Net Regressions	ART2			ART3			ART4		
	MJ30	MACQ	CUDIT	MJ30	MACQ	CUDIT	MJ30	MACQ	CUDIT
Overall Model R^2	.510	.187	.365	.583	.152	.295	.447	.210	.448
1. Use Marijuana Only Among Trusted Peers	.000	.000	.000	.201	.007	.000	.000	.000	.000
2. Avoid Use While Spending Time With Family	.000	.173	.000	.000	.258	.007	.000	.001	.000
3. Avoid Using Marijuana Before Work Or School	.000	.000	-.003	.624	.000	**-.239**	.256	-.008	**-.229**
4. Avoid Using Marijuana To Cope With Emotions Such As Sadness Or Depression	.000	-.394	-.090	.000	**-.583**	**-.268**	.457	.000	-.024
5. Limit Use To Weekends	**-2.002**	**-.471**	**-.617**	**-2.847**	**-.211**	**-.450**	**-2.353**	**-.474**	**-1.119**
6. Only Purchase Marijuana From A Trusted Source	.812	.000	.276	1.510	.000	.293	1.335	**-.543**	**-.242**
7. Avoid Using Marijuana Habitually	**-5.093**	**-.716**	**-1.883**	**-4.302**	**-.527**	**-1.583**	**-5.849**	**-.891**	**-1.758**
8. Use A Little And Then Wait To See How You Feel Before Using More	-.002	**-.241**	**-.280**	.000	-.183	-.188	.000	.000	.000
9. Avoid Mixing Marijuana With Other Drugs	.000	-.070	.045	.119	-.159	**-.267**	.000	-.185	-.175
10. Avoid Using Marijuana In Public Places	.000	**-.483**	**-.817**	.000	**-.408**	**-.220**	.000	**-.464**	**-.335**
11. Take Periodic Breaks If It Feels Like You Are Using Marijuana Too Frequently	.000	-.018	**-.448**	**-.666**	.000	-.008	.000	-.049	-.108
12. Buy Less Marijuana At A Time So You Smoke Less	.000	.324	.326	.000	.198	.509	.187	.264	.758
13. Have A Set Amount Of "Times" You Take A Hit	.000	.000	.000	.000	-.174	.000	.000	.000	.000
14. Avoid Methods Of Using Marijuana That Can Make You More Intoxicated Than You Would Like	.264	.000	.000	.000	-.059	-.079	.000	-.185	.000
15. Only Use One Time During A Day/Night	**-1.276**	.000	**-.828**	**-.719**	**-.293**	**-.546**	-.068	**-.272**	**-.238**
16. Limit The Amount Of Marijuana You Smoke In One Sitting	.000	-.091	.000	.000	.000	**-.230**	-.092	-.003	**-.234**
17. Avoid Using Marijuana Before Engaging In Physical Activity	.000	-.163	.000	**-.782**	.000	**-.386**	**-.924**	-.078	-.124

RESULTS

- The random forest models demonstrated significant predictive power, accounting for over half of the variance in cannabis use frequency (.504< R^2<.574) and substantial variance in CUD symptoms (.388<R^2<.428)
- These models explained a more modest, yet significant, amount of variance in negative cannabis-related consequences (.146<R^2<.260)
- In the random forest models, the item "Avoid using marijuana habitually (that is, every day or multiple times a week)" consistently emerged as the predictor with the highest feature importance across the three outcomes
- This item also emerged as the strongest predictor in most elastic net regression models (see Table 1) followed by "Limit use to weekends"
- Elastic net regression yielded comparable results, accounting for similar variance in cannabis use (.447< R^2<.583), CUD symptoms (.346<R^2 <.448), and negative consequences (.152<R^2<.187)
- The random forest and elastic net regression models largely identified a similar set of key predictors with small differences in predictor rankings

DISCUSSION

- We highlight items that emerged as the most robust predictors of lower cannabis-related harms (e.g., "Avoid using marijuana habitually (that is, every day or multiple times a week)," "Limit use to weekends")
- Notably, these items were both dropped from the two-factor model of the PBSM (Mian et al., YEAR)
- Notably, the hierarchy of the strongest predictors varied across the three outcome measures, suggesting that different strategies may be more or less effective depending on the specific type of harm being targeted
- These findings suggest that while PBS are broadly effective, not all strategies carry equal weight in harm reduction
- The variability of predictors across outcomes has significant implications for the development of tailored cannabis reduction and harm reduction interventions
- By focusing on the most high-impact, specific behaviors, clinicians and public health advocates can more effectively target the behaviors most likely to reduce cannabis-related problems

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