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Up in Smoke: Reciprocal Effects of Cannabis Use and Job Complexity on Extrinsic Career Outcomes

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ABSTRACT

With the passage of cannabis-friendly legislation in the U.S., cannabis use is on the rise and poses increasing challenges to managing human resources in the workplace. However, the literature offers a limited understanding of its long-term implications for career outcomes. Drawing on social selection theory, we argue that cannabis use negatively influences one's extrinsic career outcomes (i.e., income and occupational prestige) over time via lowered job complexity. Furthermore, based on social causation theory, we propose an alternative model in which higher job complexity reduces cannabis use over time to facilitate one's extrinsic career outcomes. Using 8 years of longitudinal panel data from multiple sources, we found support for the hypothesized reciprocal effect between cannabis use and job complexity and their influences on income and occupational prestige. Moreover, the impact of job complexity on extrinsic career outcomes via cannabis use was stronger than the impact of cannabis use on extrinsic career outcomes via job complexity. We discuss this study's theoretical and practical implications for cannabis use and human resource management research and practice.

1 | Introduction

Cannabis use has been a major challenge to managing human resources in the workplace. From 2017 to 2018, an increase of 7.2% of employees reported that they had used cannabis within the last month (Substance Abuse and Mental Health Services Administration 2019a). About 18% of the employees who worked full-time and another 21% of the employees who worked part-time used cannabis in 2018 (Substance Abuse and Mental Health Services Administration 2019b). A more recent survey of 46,499 respondents (18 years or older) who worked full-time showed that 15.9% of them used cannabis in the last month (Yang et al. 2024). The prevalence of cannabis use might have been fueled by many U.S. states decriminalizing medical and recreational marijuana use—although at the federal level, cannabis is still an illegal drug with a Schedule I classification (Rusby et al. 2018). Surprisingly, a recent employee safety survey from the National Safety Council revealed that fully half of companies had no written human resource (HR) policy regarding cannabis (Werk et al. 2021). The disparity between widespread cannabis use among employees and the absence of robust HR policies may stem from the dearth of relevant research in the HR literature. Our search of the main HR journals (e.g., *Human Resource Management*, *Human Resource Management Journal*, *Human Resource Management Review*, and *Personnel Psychology*) has turned up no published paper specifically devoted to this topic. Lacking scientific research, HR practitioners may have a limited understanding of the implications of cannabis use at work, which may constrain their ability to develop research-based HR policies to address this issue.

HR research regarding the workplace implications of cannabis consumption is sparse. However, research in other domains (notably economics, public health, and medicine) has examined the effect of workers' use of cannabis on employees' extrinsic career outcomes such as employment status and income. For example, Baggio et al. (2015) showed that cannabis use was positively associated with unemployment. Arria et al. (2013) found that cannabis use in college reduced the chance of being employed later in life. Boden et al. (2020) showed that heavy cannabis users had lower incomes than other types of users. Although inconsistent findings exist, most research in this literature paints a picture of the negative effect of cannabis on the user's extrinsic career outcomes.

It is important to note the theoretical and methodological limitations associated with the extant literature, which provide context for our research. First, most studies simply examine the direct effects of cannabis use on extrinsic career outcomes without concurrently examining why these effects occur (e.g., DeSimone 2002; Popovici and French 2014). This limitation is problematic because, without knowing *why* cannabis use harms individuals' careers, HR professionals may not have theoretically-grounded tools to help address this potential link. Second, the existing literature almost invariably treats cannabis use as an exogenous variable, failing to consider the possibility that work-related factors may impact employees' cannabis use, which may subsequently impact their work outcomes. This omission is curious when compared to research suggesting that alcohol abuse may be triggered by job loss (Forcier 1988). If job-related factors cause employees to consume cannabis, then HR may shift the focus from fixing the employees to fixing job-related factors. Finally, extant research is plagued by numerous methodological shortcomings, such as the use of cross-sectional data (e.g., van Ours 2006) or the use of multi-year cannabis data to predict career outcomes at a single time point (e.g., using cannabis use from the age of 18 to 38 to predict career outcomes at the age of 38; Cerdá et al. 2016), using dichotomized variables to operationalize cannabis use and employment (Teixidó-Compañó et al. 2018), and operationalizing cannabis use based on grouping of users that may be too coarse to capture the full variance of cannabis use (e.g., Augustyn et al. 2020). As noted by some reviewers of this literature (e.g., Castellanos-Ryan et al. 2021), these methodological shortcomings may explain why the connections between cannabis use and career outcomes are at times inconsistent.

To overcome these shortcomings, our study develops a longitudinal model of cannabis use and extrinsic career outcomes. Specifically, our model draws on two different theories to examine the relationships among cannabis use, job complexity, and extrinsic career outcomes. Based on social selection theory (Johnson et al. 1997), we argue that greater cannabis use may cause users to self-select or be selected into jobs that are lower in complexity. More complex jobs require incumbents to possess sophisticated problem-solving skills to solve complex and unpredictable problems and the motivation to persist in the face of repeated setbacks, ambiguous task structure, and uncertain outcomes (Liu and Li 2012; Mainert et al. 2019). Users of large amounts of cannabis, relative to non-users and users of smaller amounts, may not have the ability (can-do) and motivation (will-do) to perform highly complex jobs and as a result, drift into less complex jobs. Social selection theory is consistent with the gravitation hypothesis in general psychology, which posits that individuals are sorted into jobs that match their abilities and personality (McCormick et al. 1972). Social selection may have career implications as individuals who are clustered into more complex jobs are more likely to enjoy better extrinsic career outcomes. We focus on income and occupational prestige (e.g., Ringel et al. 2006; White et al. 2015) because they are considered two of the most robust indicators of individuals' labor market success (Judge et al. 2010). Thus, the first path of our model posits that cannabis use is positively and indirectly related to the user's extrinsic career outcomes and that the effect is mediated through the complexity level of the user's job.

Social causation theory offers an alternative possibility, suggesting that substance use represents a coping mechanism for dealing with undesirable environments (Boden et al. 2017). The alcohol abuse literature often shows that individuals use alcohol to cope with stressors in life (Rice and Van Arsdale 2010). In the same way, cannabis offers a "physiological or recreational refuge" in which users can "escape from personal or psychological problems" (Ginsberg and Greenley 1978, 24). This argument is consistent with the alienation paradigm which suggests that employees use substances in response to negative qualities of their psychosocial environment such as boredom and low decision-making latitude (Frone 1999). In the present study, we focus on job complexity, which represents a motivating work design feature (Hackman and Oldham 1980) that is associated with higher job satisfaction, lower physical demands, and less negative work conditions (Morgeson and Humphrey 2006). Job complexity was found to predict turnover intentions, suggesting that low job complexity may serve as a stressor at work, potentially leading some individuals to use cannabis as an escape (Joo et al. 2015). Cannabis use as a risk factor may cause employees to experience suboptimal career outcomes (e.g., Green et al. 2017; Thompson et al. 2019). Thus, the second path of our model posits that job complexity is positively and indirectly related to the user's extrinsic career outcomes, and the effect is mediated through cannabis use.

Our study advances the literature by elucidating the complex interplay between cannabis use, job complexity, and career outcomes, offering critical insights for HR practices. First, by focusing on job complexity as a predictor of cannabis use, we address the "erroneous assumption that substance abuse is not itself affected by one's employment status, an assumption that should be revised" (Henkel 2011, 17). Our study is also unique in that we focus on specific attributes of the job as a predictor of substance use as opposed to employment status (Henkel 2011). This distinction is important because while unemployed individuals are not within the purview of the HR department, employees who turn to cannabis due to low job complexity are. Our study also contributes to the job complexity literature, which tends to focus on its impact on work outcomes without considering its impact on non-work behaviors (e.g., Chae and Choi 2018; Joo and Lim 2009).

Second, we examine the reciprocal relationships between cannabis use and job complexity as they are both related to extrinsic career outcomes. Though some studies may suggest a possible bi-directional effect, they are limited in scope and methodology. For example, Boden et al. (2017) examined the bi-directional relationship between cannabis use and unemployment without considering potential mediating processes. Most importantly, we explicitly examine the relative strength of the two distinct paths in our model. This is an important consideration because if cannabis use is triggered by certain features of the work itself (more so than the other way around), then interventions that focus solely on users (rather than work attributes) may be ineffective.

Finally, our study addresses many of the methodological challenges found in prior research. Specifically, we took a longitudinal approach, using 8 years of longitudinal panel data, which came from multiple sources. Analytically, we used cross-lagged panel regression to examine the lagged impact of a predictor at Time T on an outcome variable at Time $T+1$ while accounting for the effect of the outcome variable's previous rating at Time T. We also conducted a series of robustness tests to ensure the validity of our findings.

2 | Theory and Hypotheses

2.1 | Cannabis Use as a Predictor of Job Complexity

Social selection theory from the substance abuse literature proposes that substance abuse may place individuals at greater risk for various unfavorable life outcomes, such as homelessness and unemployment (Johnson et al. 1997). The underlying reason is that substance abuse may distribute people into different social strata based on their ability, with heavier substance use resulting in a greater downward drift (Benda 1987). Social selection theory thus explains how substance abuse may impact individuals' employment participation, including whether they are employed and what types of occupations they go into. Social selection theory is consistent with the gravitation hypothesis, which posits that people gravitate towards jobs that are compatible with their values and abilities (Wilk and Sackett 1996). Empirical research has provided support for social selection theory. For example, Zhang et al. (2016) found that groups classified as chronic cannabis users over a span of 29 years were more likely to be unemployed in their early 40s in comparison to other groups (such as non-users). Arria et al. (2013) found that persistent cannabis users throughout college were more likely to be unemployed or to work part-time than non-users. However, none of these studies examined the specific attributes of the job that users are selected into as a result of cannabis use.

Drawing on social selection theory, we predict that higher levels of cannabis consumption may steer users towards jobs with lower complexity. Job complexity is defined as the extent to which a job involves constant changes, the use of high levels of intellectual ability, and the "synthesis or interpretation of complex data" (Oswald et al. 1999, 3). Highly complex jobs require incumbents to possess a high level of ability, especially cognitive ability. That is because these jobs require them to acquire new and complex skillsets, process a large amount of information, and adapt to constant changes in the task environment (Jundt et al. 2015). At the same time, highly complex jobs also require job incumbents to maintain a high level of motivation that allows them to persist even in the face of failures, task ambiguity, and difficulties (Sturman et al. 2005; Wilk and Sackett 1996).

Cannabis use may impair both the "can-do" and "will-do" aspects of the users, diminishing their suitability for complex jobs. Can-do refers to employees' *ability* to perform a certain task, whereas will-do refers to employees' *motivation* to perform a task (Huang et al. 2019). From the perspective of can-do, past research has suggested that cannabis contains psychoactive ingredients that may reduce users' cognitive functioning both in the short term and in the long term (Scott et al. 2018; Yanes et al. 2018). Broadly, frequent use of cannabis from adolescence into adulthood is related to declines in general mental ability (Volkow et al. 2014), which is critical to job performance in high-complexity jobs (Schmidt and Hunter 2004). Specifically, heavy cannabis use may alter brain structure and function (Matochik et al. 2005), creating memory and concentration issues and impairing the ability to think creatively and learn new knowledge and skills (Lundqvist 2005). Since more complex jobs have higher cognitive resource demands, heavier cannabis use may reduce the cognitive resources of users resulting in them selecting themselves or being selected into less complex jobs that place a lower demand on their cognitive functioning.

From the perspective of will-do, cannabis users may lack aspirations to succeed, deemphasize employment achievements, and affiliate with delinquent peers (Arria et al. 2013). Scholars have termed this "amotivational syndrome" (McGlothlin and West 1968), which refers to the tendency of cannabis users to become withdrawn and unmotivated and experience a reduction in their capacity to "carry out complex, long-term plans" (Ringel et al. 2006, 61). Supporting this argument, longitudinal research has found that those who were classified as involved users (who used cannabis multiple times in several follow-up surveys) reported significantly lower work commitment than those who were classified into other categories such as abstaining or experimental users (Hyggen 2012; also see Brook et al. 2013). Similarly, Brook et al. (2002) found that cannabis use was associated with lower subsequent occupational expectations. Even after accounting for tobacco and alcohol use, research has shown that cannabis use is linked to decreased initiative and persistence (Lac and Luk 2018). Given that highly complex jobs require high levels of conscientiousness (Le et al. 2011) and achievement motivation (Judge et al. 2000), cannabis users may be sorted into less complex jobs. As Ng and Feldman (2009) noted, highly complex jobs require "strong motivation and persistence to excel" (p. 96), which may be lacking among those who consume larger amounts of cannabis.

Hypothesis 1a. *There is a negative time-lagged relationship between cannabis use and job complexity.*

Extrinsic career outcomes represent work elements motivating employees to perform at a higher level, which may have important implications for the competitiveness of the organization (Huselid 1995; Judge et al. 1995). Past research has suggested that complex jobs are associated with higher extrinsic career outcomes (e.g., Gonzalez-Mule et al. 2017). Complex jobs tend to be difficult to perform as they require high levels of cognitive ability to synthesize a large amount of information, to constantly adjust to changing conditions, and to acquire and use complex skills and knowledge (Converse et al. 2014). Complex jobs are also characterized by higher levels of ambiguity by requiring more effort and perseverance on the part of incumbents (Chung-Yan 2010). Finally, highly complex jobs are more likely to promote creativity and innovation as incumbents look to generate greater economic and social impact for the organizations in which they work (Shalley et al. 2009). Since complex jobs tend to provide firms with more competitive advantage, incumbents are likely to be better compensated and accorded higher occupational prestige (Gonzalez-Mule et al. 2017). This argument is consistent with Becton et al. (2011) who suggested that people who have more complex jobs tend to have more opportunities and job options. Because replacing them is difficult, organizations may invest more in them in terms of pay and job prestige (Becton et al. 2017). The positive association between job complexity and extrinsic career outcomes has been demonstrated in past research (e.g., Gonzalez-Mule et al. 2017; Judge et al. 2010). Thus, greater cannabis use may lead to the selection of heavy users into jobs with lower complexity. In turn, lower job complexity may lead to worse extrinsic career outcomes.

Hypothesis 1b. *There is a positive time-lagged relationship between job complexity and extrinsic career outcomes.*

Hypothesis 1c. *There is a negative, time-lagged, indirect relationship between cannabis use and extrinsic career outcomes that is mediated through job complexity.*

2.2 | Job Complexity as a Predictor of Cannabis Use

Social selection theory, as described above, suggests that cannabis use may result in a lower level of job complexity for users. It is also important to consider the possibility that lower job complexity may cause employees to turn to cannabis use as an escape. Social causation theory proposes that unfavorable environmental factors may cause individuals to experience mental or physical disorders (Hollingshead and Redlich 1958). For example, growing up in poverty may increase the odds of individuals living a disadvantaged life later and developing psychological and physical health issues (Simmons et al. 2008). This argument aligns with the stressor theory in the substance abuse literature, which shows that unemployment increases substance use (Castellanos-Ryan et al. 2021). It also aligns with the alienation paradigm in general psychology, which asserts that an undesirable work environment may trigger substance abuse (Frone 2008). There is some empirical support to these arguments in substance use studies. For example, Mossakowski (2008) found that the duration of unemployment from 1979 to 1991 was positively related to the frequency of heavy drinking in 1992; Boden et al. (2017) found that unemployment was associated with increased odds of cannabis dependence. However, there has been no research on how specific job attributes impact cannabis use. This omission is surprising because job attributes play an essential role in predicting employees' reactions to job characteristics.

Based on social causation theory, we argue that working in highly complex jobs may lead to lower cannabis use because these jobs tend to offer significant psychological benefits to incumbents, thereby precluding the need to use cannabis as a coping response. First, these jobs tend to come with a high level of autonomy, which is desirable because they give the incumbents much latitude in determining when and how to carry out job duties (Gonzalez-Mule et al. 2017). Second, according to the job characteristics model (Hackman and Oldham 1980), jobs that are highly complex tend to be motivating, as they are more likely to impact firm outcomes in tangible and meaningful ways. Since incumbents are directly responsible for these outcomes, they are more likely to experience task significance which is an important hallmark of a highly motivating job (Converse et al. 2014; Gonzalez-Mule et al. 2017). Third, these jobs tend to be intrinsically enriching and rewarding, exposing incumbents to new stimuli and possibilities in complex work activities. Supporting these arguments, past research has shown that job complexity is positively related to job satisfaction (Humphrey et al. 2007; Judge et al. 2000), suggesting that solving complex problems at work may make the job “fulfilling and satisfying” (Gonzalez-Mule et al. 2017, 158). By contrast, low complexity is a central feature of jobs with a Taylorism human resource management approach in which tasks are repetitive and mechanic (Zacher and Frese 2011) and may expose incumbents to a variety of work stressors such as monotony, lack of autonomy, limited professional opportunities, low decision-making latitude, and minimal impact or task significance (Chae and Choi 2018; Zacher and Frese 2011). Zacher and Frese (2011) described such jobs as not preparing incumbents for the future and potentially fostering the perception that they are stuck in a dead-end job. Overall, individuals in low complexity jobs may experience a lack of fulfillment and increased stress, leading them to use cannabis as an escape from the reality of work.[1]

Hypothesis 2a. *There is a negative time-lagged relationship between job complexity and cannabis use.*

Cannabis use may reduce individuals' concentration and judgment (Howard and Osborne 2020; Lynskey and Hall 2000), which may impair their work productivity. High cannabis use may also impact work attendance as users are often too impaired cognitively and emotionally to be able to report to work (Normand et al. 1990). Cannabis use may signal a lack of sound judgment and a failure to adhere to rules and regulations, which is antithetical to the espoused values of most employers (Ng and Feldman 2009) and could harm the social standing of users. These arguments together suggest that cannabis use may lower individuals' extrinsic career outcomes. Past research has offered empirical evidence on this link (Ringel et al. 2006). For example, in a 10-year prospective study on 662 youths, Thompson et al. (2019) found that chronic users who increased their cannabis use from adolescence to young adulthood had lower occupational prestige in young adulthood relative to those who abstained from or decreased their cannabis use. These individuals also reported lower incomes. Using a prospective study, Braun et al. (2000) found that among Whites (but not among Blacks), cannabis use was negatively associated with occupational prestige and family income. Thus, higher job complexity is associated with lower cannabis consumption which in turn is associated with higher extrinsic career outcomes.

Hypothesis 2b. *There is a negative time-lagged relationship between cannabis use and extrinsic career outcomes.*

Hypothesis 2c. *There is a positive, time-lagged, indirect relationship between job complexity and extrinsic career outcomes that is mediated through cannabis use.*

2.3 | Relative Strength

In the previous sections, we propose two causal pathways. Based on social selection theory, we propose that cannabis is indirectly and negatively related to users' extrinsic career outcomes, and this effect is mediated through job complexity. Based on social causation theory, we alternatively propose that job complexity is indirectly and positively related to employees' extrinsic career outcomes, and this effect is mediated through cannabis use. Given the prediction that cannabis use and job complexity are reciprocally related, we further investigate which effect is stronger. There are both theoretical and empirical reasons to believe that the strength of the relationship between job complexity and cannabis use will be greater than the strength of the relationship between cannabis use and job complexity. From a theoretical standpoint, employees have more control over their use of cannabis (as a response to job complexity) than their control over the complexity of the job as a response to cannabis use. For example, even if employees decrease their cannabis use, moving into a more complex job subsequently may be difficult because these jobs often require additional education. Upward moves, relatively speaking, may also be constrained by the availability of job openings. In addition, selecting downward (increases in cannabis use resulting in being selected into jobs that are lower in complexity) may be slow to realize due to factors such as organizational inertia, organizational tenure, and union protection (Wilk and Sackett 1996). Empirically, past research on the effects of cannabis use on employment outcomes has been somewhat mixed. In a review of the literature, Castellanos-Ryan et al. (2021) suggest that "the specific impact of cannabis use may be minimal from an ecological perspective" (p. 14).

Hypothesis 3. *The lagged effect of job complexity on cannabis use is stronger than the lagged effect of cannabis use on job complexity.*

3 | Method

3.1 | Sample and Data

We used data from the National Longitudinal Survey of Youth 1997 (NLSY97), a longitudinal panel study of American youths. Participants were ages 12 to 18 when they were first interviewed in 1997–1998. The entire study consisted of 19 rounds of interviews, conducted annually from 1997 to 2011 and biannually afterwards (2013, 2015, 2017, and 2019). The initial sample included 8984 individuals (49% females). We established three exclusion criteria for our study. First, because our study examines the reciprocal relationship between cannabis use and employment outcomes, we followed past research by only focusing on individuals who were 18 or older (e.g., Kaestner 1994). We also used the age of 18 because, based on a prior population-level survey (Substance Abuse and Mental Health Services Administration 2012), it is the average age at which people begin to use cannabis. Thus, our study period started in 2003 when even the youngest initial participants of the study reached 18. Second, we excluded the 2011 data because the income data for that year was not available (there was no NLSY97 survey in 2012 that asked about 2011 income).[2] We also excluded the study waves after 2011 because cannabis use was not included in the 2013, 2017, or 2019 surveys. Thus, only the data from the study period of 2003–2010 was used in our analysis, resulting in a total of eight waves of annual data (from T1 to T8). Third, we excluded individuals who did not provide any response to the variables among the eight waves of data. Response rates for each data wave in this study varied from 82.4% to 87.9%. The final sample included a total of 3525 individuals.[3] Among them, 43.8% were female, 61.3% were White, 25.7% were Black, 0.8% were American Indian, 1.7% were Asian, and 10.5% were other ethnicities. At the beginning of the 8-year study period, participants had an average age of 20.16 (SD = 1.49) and a range of 18–24. About 33% of the participants were enrolled in school in 2003, and the percentage went down to 12% in 2010. As attending school may constrain occupational choices, we addressed the influence of school enrollment in our supplementary analysis.

3.2 | Study Measures

Cannabis use. In the self-administered portion of the interview, participants responded to a question about the number of days they used cannabis over the last 30 days. This method treats the frequency of cannabis use by participants as a continuous variable and offers advantages over dichotomizing cannabis use (heavy vs. non-heavy users) as has often been done in prior research (e.g., Caulkins et al. 2020).

Job complexity. In the NLSY97, participants self-reported their occupations, and their responses were coded based on the Standard Occupational Classification (SOC).[4] We first used the O*NET crosswalk to convert SOC codes into O*NET-SOC codes and then operationalized job complexity level with the O*NET variable, job zone, which captures the levels of education and experience that are required. The measure includes five levels, ranging from 1 (little to no preparation needed) to 5 (extensive preparation needed). Each job zone rating represents the combined judgment of four trained job analysts (for full details on how job zone ratings were determined see Procedures for O*NET job zone assignment 2008). This operationalization is consistent with Oswald et al. (1999, 4) who used specific vocational preparation to capture job complexity and other studies using the O*NET variable "job zone" as a measure of job complexity (e.g., Brown et al. 2023; Converse et al. 2014; Le et al. 2011).

Extrinsic career outcomes. Following Judge et al. (2010), we used two indicators of extrinsic career outcomes: income and occupational prestige. Participants reported their total income in US dollars for the previous year (e.g., in the 2004 NLSY interview, they reported their total income in 2003). Due to skewness, we applied a natural log transformation on the reported income to facilitate the subsequent analysis. For occupational prestige, we followed Judge et al. (2010; also see Huang et al. 2019) by converting SOC codes into scores on the Duncan Socioeconomic Index (SEI, Duncan 1961). SEI scores ranged from 3 to 96, with higher scores indicating higher levels of occupational prestige. As Judge et al. (2010) pointed out, although the original SEI was created decades ago, research has suggested that there has been little change over time (Hauser and Warren 1997).

3.3 | Analytical Strategies

We used M*plus* Version 8.6 (Muthén and Muthén, 1998–2017) to test our hypothesized model with a robust maximum likelihood estimator. Missing data were handled with full information maximum likelihood. Because our hypotheses focus on between-person variability in the study variables, we applied an autoregressive cross-lagged panel model (Bollen and Curran 2006; Little 2013; Orth et al. 2021) to examine the relationships among cannabis use, job complexity, and extrinsic career outcomes. For example, we are interested in how differences in cannabis use between individuals at T1 may impact the person's rank order in job complexity at T2. We examined the distribution and significance of indirect effects using 5000 bootstrapped samples (Hayes 2009). When comparing the strength of indirect effects, we followed Hayes (2018) to establish the confidence interval for the difference between the absolute values of indirect effects that were being compared; a confidence interval not containing zero suggests a significant difference. For model comparison, we used multiple fit indices as references. Given that our sample size is relatively large ($N = 3525$) and the Chi-square test is sensitive to sample size (Chen 2007; Cheung and Rensvold 2002), we also used ΔCFI or ΔTLI < 0.010 and ΔRMSEA < 0.015 as a recommended threshold of no significant change in model fit (Chen 2007; Cheung and Rensvold 2002; Li et al. 2021) that favors the more parsimonious model.

4 | Results

4.1 | Results of Hypothesis Testing

Table 1 presents descriptive statistics of study variables. Before we tested our hypotheses, we first examined whether the hypothesized structural model (see Figure 1) adequately represented the data. Table 2 summarizes model fit information and the results of the comparison between tested models. We built Model 1 to represent our conceptual model that freely estimated all model parameters. The model showed a good fit to the data. From Model 2 to Model 4, we tested a series of more stringent models that constrained like paths to be equal over time. Specifically, Model 2 tested whether the autoregressive effect of the same underlying variable (e.g., the effect of cannabis use at T_n on that at T_{n+1}) was equal, Model 3 tested whether like relationships between different variables (e.g., the effect of cannabis use at T_n on job complexity at T_{n+1}) were equal, and Model 4 tested whether the covariances among different variables at the same time point (e.g., the covariance between cannabis use at T_n and job complexity at T_n) were equal. All these models showed adequate fit to the data, and model comparison based on the results of ΔRMSEA, ΔCFI, and ΔTLI supported Model 4, which included all equal parameter constraints tested by prior models.

We continued to test the robustness of Model 4 by examining alternative models. As shown in Table 2, Model 5 added to Model 4 the direct effect of cannabis use and job complexity at T_n on total income and occupational prestige at T_{n+2}. Although this model showed adequate model fit, the result of model comparison favored the more parsimonious Model 4, and as a result, we did not include the direct effects. Compared to Model 4, Model 6 added the effects of total income and occupational prestige on cannabis use and job complexity. The results of model comparison did not support adding these reciprocal effects. In Model 7, we tested if there was a reciprocal effect among measures of total income and occupational prestige, but Model 7 was not favored when compared with Model 4. Finally, in Model 8, we removed all hypothesized relationships between variables and only retained the autoregressive effect of the same underlying variables over time. Model 8 yielded significantly decreased fit than Model 4. Therefore, we retained Model 4 as the basis to evaluate our conceptual model.

Figure 2 illustrates the results of our hypothesized model. The model fitted the data well: $\chi^2 = 2105.249$, df = 480, RMSEA [90% CI] = 0.031 [0.030, 0.032], CFI = 0.935, TLI = 0.933. Hypothesis 1a proposed that cannabis use would be negatively related to job complexity between adjacent times. This hypothesis was supported as cannabis use negatively predicted job complexity ($b = -0.004$, SE = 0.001, $p < 0.001$). Hypothesis 1b proposed the positive lagged effect of job complexity on extrinsic career outcomes. We found that job complexity was positively related to total income ($b = 0.14$, SE = 0.01, $p < 0.001$) and occupational prestige ($b = 0.60$, SE = 0.15, $p < 0.001$). Thus, Hypothesis 1b was supported. Hypothesis 2a proposed that job complexity would negatively predict cannabis use at a later time point. We found support for this hypothesis ($b = -0.73$, SE = 0.10, $p < 0.001$). Hypothesis 2b suggested that cannabis use would be negatively related to extrinsic career outcomes. The results showed that cannabis use was negatively associated with total income ($b = -0.005$, SE = 0.001, $p < 0.001$) and occupational prestige ($b = -0.05$, SE = 0.01, $p < 0.001$). Thus, Hypothesis 2b was supported.

Finally, we used 5000 bootstrapped samples to test the hypothesized indirect effect. Hypothesis 1c and Hypothesis 2c respectively argued for the mediating role of job complexity and cannabis use in influencing extrinsic career outcomes. Table 3 presents the indirect effects and their 95% confidence intervals. We found that job complexity mediated the lagged negative effect of cannabis use on total income (*estimate* = −0.0005, 95% CI = [−0.0007, −0.0004]) and occupational prestige (*estimate* = −0.002, 95% CI = [−0.004, −0.001]). Thus, Hypothesis 1c was supported. We found support for Hypothesis 2c, as the positive indirect effects of job complexity on total income (*estimate* = 0.004, 95% CI = [0.002, 0.006]) and occupational prestige (*estimate* = 0.033, 95% CI = [0.019, 0.051]) via cannabis use were significant. To test Hypothesis 3, we examined the relative strengths between the indirect effect of job complexity and cannabis use on extrinsic career outcomes. We found that

TABLE 1 | Descriptive statistics of study variables.

	Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12
1. Cannabis use T1	9.83	11.49												
2. Cannabis use T2	10.08	11.70	0.61**											
3. Cannabis use T3	9.85	11.52	0.55**	0.62**										
4. Cannabis use T4	10.17	11.65	0.51**	0.55**	0.61**									
5. Cannabis use T5	10.48	11.72	0.48**	0.53**	0.54**	0.65**								
6. Cannabis use T6	10.96	11.85	0.38**	0.46**	0.49**	0.55**	0.63**							
7. Cannabis use T7	11.92	12.18	0.45**	0.39**	0.49**	0.53**	0.55**	0.63**						
8. Cannabis use T8	12.13	12.40	0.44**	0.39**	0.42**	0.45**	0.49**	0.54**	0.59**					
9. Job complexity T1	2.22	0.75	−0.07**	−0.09**	−0.04	−0.13**	−0.11**	−0.10**	−0.11**	−0.07*				
10. Job complexity T2	2.29	0.80	−0.07*	−0.09**	−0.08**	−0.10**	−0.09**	−0.07*	−0.06	−0.08*	0.60**			
11. Job complexity T3	2.39	0.84	−0.11**	−0.09**	−0.07*	−0.10**	−0.13**	−0.08*	−0.10**	−0.10**	0.43**	0.65**		
12. Job complexity T4	2.45	0.90	−0.07*	−0.09**	−0.08**	−0.09**	−0.14**	−0.08*	−0.05	−0.10**	0.35**	0.51**	0.70**	
13. Job complexity T5	2.54	0.95	−0.13**	−0.14**	−0.11**	−0.15**	−0.17**	−0.16**	−0.14**	−0.12**	0.34**	0.47**	0.53**	0.72**
14. Job complexity T6	2.59	0.97	−0.16**	−0.14**	−0.13**	−0.15**	−0.13**	−0.13**	−0.12**	−0.10**	0.31**	0.42**	0.46**	0.58**
15. Job complexity T7	2.63	1.00	−0.15**	−0.12**	−0.11**	−0.18**	−0.16**	−0.13**	−0.15**	−0.14**	0.28**	0.39**	0.44**	0.53**
16. Job complexity T8	2.68	1.03	−0.15**	−0.11**	−0.10**	−0.16**	−0.14**	−0.12**	−0.15**	−0.14**	0.28**	0.38**	0.39**	0.50**
17. Total income T1	9.00	1.41	0.05	0.02	−0.01	0.04	0.05	0.01	−0.003	0.02	0.10**	0.08**	0.02	0.05
18. Total income T2	9.30	1.19	−0.09**	−0.02	−0.03	0.02	−0.01	0.02	−0.05	−0.09*	0.06*	0.12**	0.10**	0.06*
19. Total income T3	9.49	1.19	−0.01	−0.04	−0.06*	−0.02	−0.01	0.02	−0.02	−0.03	0.05*	0.11**	0.10**	0.08**
20. Total income T4	9.61	1.40	−0.03	−0.08*	−0.08**	−0.03	−0.07*	−0.06	−0.03	−0.07	0.10**	0.16**	0.15**	0.22**
21. Total income T5	9.83	1.19	−0.09**	−0.06	−0.11**	−0.05	−0.06	−0.05	−0.06	−0.08*	0.11**	0.12**	0.14**	0.20**
22. Total income T6	9.90	1.22	−0.07*	−0.06*	−0.09**	−0.09**	−0.11**	−0.06	−0.10**	−0.07*	0.14**	0.18**	0.22**	0.26**
23. Total income T7	9.87	1.36	−0.08**	−0.08*	−0.12**	−0.15**	−0.13**	−0.06	−0.15**	−0.08*	0.13**	0.16**	0.19**	0.24**
24. Total income T8	9.99	1.23	−0.08**	−0.09**	−0.07*	−0.11**	−0.14**	−0.08*	−0.12**	−0.04	0.13**	0.20**	0.20**	0.25**
25. Occupational prestige T1	32.74	8.57	−0.08*	−0.08*	−0.02	−0.13**	−0.06	−0.10*	−0.09*	−0.08	0.70**	0.37**	0.24**	0.20**
26. Occupational prestige T2	33.68	9.08	−0.07*	−0.07*	−0.03	−0.09*	−0.04	−0.09*	−0.03	−0.07	0.41**	0.74**	0.41**	0.33**

(Continues)

TABLE 1 | (Continued)

	Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12
27. Occupational prestige T3	35.04	9.37	−0.07*	−0.05	−0.01	−0.01	−0.04	−0.002	−0.01	−0.03	0.31**	0.46**	0.75**	0.49**
28. Occupational prestige T4	35.81	10.06	−0.03	−0.03	−0.05	−0.05	−0.10*	−0.03	−0.04	−0.01	0.25**	0.36**	0.48**	0.78**
29. Occupational prestige T5	36.85	10.39	−0.13**	−0.11**	−0.02	−0.09*	−0.10**	−0.08	−0.09*	−0.06	0.28**	0.36**	0.40**	0.56**
30. Occupational prestige T6	37.40	10.72	−0.14**	−0.08*	−0.03	−0.09*	−0.05	−0.05	−0.05	−0.04	0.22**	0.32**	0.36**	0.46**
31. Occupational prestige T7	37.74	11.25	−0.13**	−0.07	−0.01	−0.15**	−0.10*	−0.05	−0.13**	−0.07	0.25**	0.33**	0.37**	0.46**
32. Occupational prestige T8	38.76	11.57	−0.12**	−0.09*	−0.03	−0.14**	−0.09*	−0.06	−0.13**	−0.13**	0.23**	0.31**	0.31**	0.43**

	13	14	15	16	17	18	19	20	21	22	23	24	25	26
14. Job complexity T6	0.76**													
15. Job complexity T7	0.66**	0.83**												
16. Job complexity T8	0.62**	0.69**	0.81**											
17. Total income T1	0.02	−0.02	−0.03	−0.05										
18. Total income T2	0.003	−0.01	−0.03	−0.02	0.47**									
19. Total income T3	0.04	0.04	0.03	0.03	0.35**	0.55**								
20. Total income T4	0.14**	0.11**	0.09**	0.10**	0.29**	0.39**	0.51**							
21. Total income T5	0.19**	0.15**	0.12**	0.12**	0.21**	0.32**	0.39**	0.45**						
22. Total income T6	0.25**	0.26**	0.24**	0.21**	0.18**	0.25**	0.32**	0.33**	0.49**					
23. Total income T7	0.24**	0.22**	0.24**	0.24**	0.17**	0.16**	0.25**	0.27**	0.34**	0.44**				
24. Total income T8	0.26**	0.28**	0.27**	0.26**	0.16**	0.23**	0.25**	0.30**	0.35**	0.40**	0.45**			
25. Occupational prestige T1	0.21**	0.21**	0.18**	0.20**	0.15**	0.17**	0.11**	0.16**	0.15**	0.12**	0.17**	0.12**		
26. Occupational prestige T2	0.31**	0.27**	0.20**	0.28**	0.15**	0.20**	0.15**	0.20**	0.13**	0.20**	0.14**	0.18**	0.61**	
27. Occupational prestige T3	0.34**	0.26**	0.24**	0.24**	0.09**	0.17**	0.15**	0.23**	0.16**	0.21**	0.17**	0.16**	0.45**	0.66**
28. Occupational prestige T4	0.49**	0.37**	0.33**	0.34**	0.10**	0.16**	0.14**	0.25**	0.23**	0.25**	0.21**	0.24**	0.39**	0.52**
29. Occupational prestige T5	0.80**	0.57**	0.48**	0.44**	0.08*	0.12**	0.11**	0.18**	0.21**	0.29**	0.25**	0.28**	0.36**	0.46**
30. Occupational prestige T6	0.55**	0.80**	0.65**	0.51**	0.03	0.10**	0.08**	0.17**	0.23**	0.33**	0.27**	0.29**	0.33**	0.40**
31. Occupational prestige T7	0.52**	0.66**	0.81**	0.65**	0.03	0.05	0.13**	0.15**	0.17**	0.31**	0.29**	0.32**	0.37**	0.39**
32. Occupational prestige T8	0.48**	0.55**	0.67**	0.82**	−0.001	0.02	0.10**	0.16**	0.12**	0.24**	0.29**	0.30**	0.33**	0.38**

TABLE 1 | (Continued)

	27	28	29	30	31
28. Occupational prestige T4	0.71**				
29. Occupational prestige T5	0.55**	0.75**			
30. Occupational prestige T6	0.45**	0.64**	0.81**		
31. Occupational prestige T7	0.47**	0.61**	0.72**	0.88**	
32. Occupational prestige T8	0.43**	0.58**	0.64**	0.76**	0.87**

Note: $N = 1193$–2506. Total income was natural log transformed. $^*p < 0.05$, $^{**}p < 0.01$.

in comparison with the indirect effect of cannabis use via job complexity, job complexity showed a stronger influence on total income (*estimate* = 0.003, 95% CI = [0.002, 0.006]) and occupational prestige (*estimate* = 0.030, 95% CI = [0.017, 0.048]) via cannabis use. These results supported Hypothesis 3.

4.2 | Results of Supplementary Analyses

We conducted a number of supplementary analyses to assess the robustness of our findings. First, we performed endogeneity tests of the bidirectional relationship between cannabis use and job complexity. Specifically, we employed two sets of tests: two-stage least squares regression (2SLS) with instrument variables and two matching approaches (propensity score matching [PSM] and coarsened exact matching [CEM]). Results of these analyses are reported in Appendix A. Overall, these results offer strong support for the associations between cannabis use and job complexity even after accounting for endogeneity.

Second, we tested a model that included time-varying variables (from 2003 to 2010), including individual alcohol use (measured in the number of days one or more drinks of alcohol were consumed in the last 30 days), general health status (participants were asked about their general health, with scores ranging from 1 [excellent] to 5 [poor]; we reverse-coded the data so that higher scores indicated better health), body mass index (BMI, calculated from participants' self-report of their height and weight), and annual work hours (calculated as the natural logarithm transformation of the total number of hours worked during the year). We controlled for these variables because past research has shown that cannabis use is related to alcohol use (e.g., Yurasek et al. 2017) and health conditions (e.g., van Ours and Williams 2015). We also controlled for work hours due to their relationships with extrinsic career outcomes (e.g., Bick et al. 2018). We regressed these control variables on all study variables at the corresponding time point. The model showed adequate fit ($\chi^2 = 3830.828$, df = 1376, RMSEA [90% CI] = 0.022 [0.022, 0.023], CFI = 0.930, TLI = 0.922), and the pattern of results remained unchanged (see Appendix B).

Third, cross-lagged models typically do not include time-invariant controls (Liu et al. 2016, 385; Eby et al. 2015, 1278; Wayne et al. 2022). Nevertheless, we tested a model that included time-invariant variables, including individual age, gender, race, education in Year 2010 (operationalized as grade completed), family income, and parents' education (operationalized as grade completed). These variables were included as controls because past research has linked them to cannabis use (age: Haug et al. 2017; gender: Tu et al. 2008; race: Keyes et al. 2017; education: Lynskey and Hall 2000; parental income: Daniel et al. 2009; parental education: Rungo et al. 2015). We regressed study variables measured at the first time point on these control variables. The model fit was acceptable ($\chi^2 = 3488.852$, df = 676, RMSEA [90% CI] = 0.034 [0.033, 0.035], CFI = 0.906, TLI = 0.900), and the same pattern of results emerged (see Appendix C). In addition, we controlled for the impact of intelligence on job complexity in a separate model. This is because individual intelligence can influence what types of work a person is capable of, thus potentially influencing job complexity. Three different intelligence

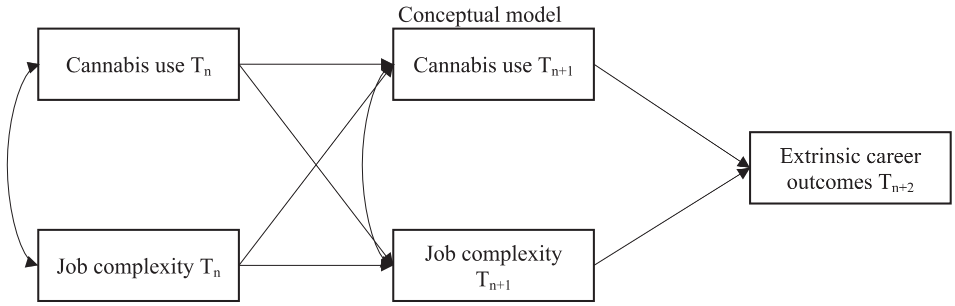

FIGURE 1 | Conceptual model. T_n represents any time points between T1 and T8 in this study, and T_{n+1} and T_{n+2} represent the following two time points.

TABLE 2 | Results of model comparison.

	Scaling	χ^2	df	RMSEA [90% CI]	CFI	TLI	$\Delta\chi^2$	Δdf	ΔRMSEA	ΔCFI	ΔTLI
Model 1	1.155	1654.779	378	0.031 [0.029, 0.032]	0.949	0.933	—	—	—	—	—
Model 2	1.316	1830.671	402	0.032 [0.030, 0.033]	0.943	0.930	129.264	24	0.001	−0.006	−0.003
Model 3	1.293	1918.934	438	0.031 [0.030, 0.032]	0.940	0.933	69.608	36	−0.001	−0.003	0.003
Model 4	1.296	2105.249	480	0.031 [0.030, 0.032]	0.935	0.933	186.261	42	0.000	−0.005	0.000
Model 5	1.310	2032.798	456	0.030 [0.030, 0.032]	0.937	0.932	63.851	24	0.001	−0.002	0.001
Model 6	1.314	2045.449	452	0.032 [0.030, 0.033]	0.936	0.931	41.288	28	−0.001	−0.001	0.002
Model 7	1.307	2013.409	466	0.031 [0.029, 0.032]	0.938	0.935	103.387	14	0.000	−0.003	−0.002
Model 8	1.295	2378.389	486	0.033 [0.032, 0.035]	0.924	0.923	298.356	6	0.002	−0.011	−0.010

Note: $N = 3525$. Scaling correction was applied to compute chi-square difference scores (Satorra and Bentler 2010).
Abbreviations: CFI = comparative fit index, RMSEA = root mean square error of approximation, TLI = Tucker–Lewis Index.

indicators (i.e., ACT score in 2007, SAT math score in 2007, and SAT verbal score in 2007) were respectively used in the analyses, and the model results were unchanged.

Fourth, we conducted multiple-group analyses to examine whether the effects differ as a function of gender and race (White vs. non-White). This analysis is different from the analysis above that included gender and race as control variables. Specifically, by using multi-group analysis, we were able to determine whether the specific paths of our model varied by gender and race. The results of these analyses are shown in Appendix D. None of the comparisons was statistically significant, suggesting no difference was found as a function of gender and race.

Fifth, young adults enrolled in colleges and universities may have limited occupational options due to their time commitment to schoolwork. As such, we conducted two additional analyses (see Appendix E) to evaluate if our findings would remain the same after accounting for school enrollment status. In the first analysis, we controlled the effect of enrollment status as a time-varying variable on study variables in the original model. In the second analysis, we recoded participants' work-related data (i.e., job complexity, total income, and occupational prestige) in a year as missing when he/she was enrolled in school that year. In both analyses, the pattern of results remained the same as the original model.

Finally, though job complexity is often theorized to be a desirable work characteristic (Morgeson and Humphrey 2006), high job complexity could also elevate the level of stress employees experience (e.g., Chung-Yan 2010) thereby causing job incumbents to turn to cannabis use as a coping mechanism. To see if this was the case in our data, we tested the curvilinear effect of job complexity on cannabis use by adding the square of job complexity (second-order term) as an additional predictor of cannabis use together with the main effect of job complexity (first-order term). Though the curvilinear effect was significant on cannabis use ($b = -0.193$, $SE = 0.076$, $p < 0.05$), the model showed a poor fit to the data ($\chi^2 = 7569.044$, $df = 675$, RMSEA [90% CI] = 0.054 [0.053, 0.055], CFI = 0.818, TLI = 0.815), making the observed curvilinear effect uninterpretable.

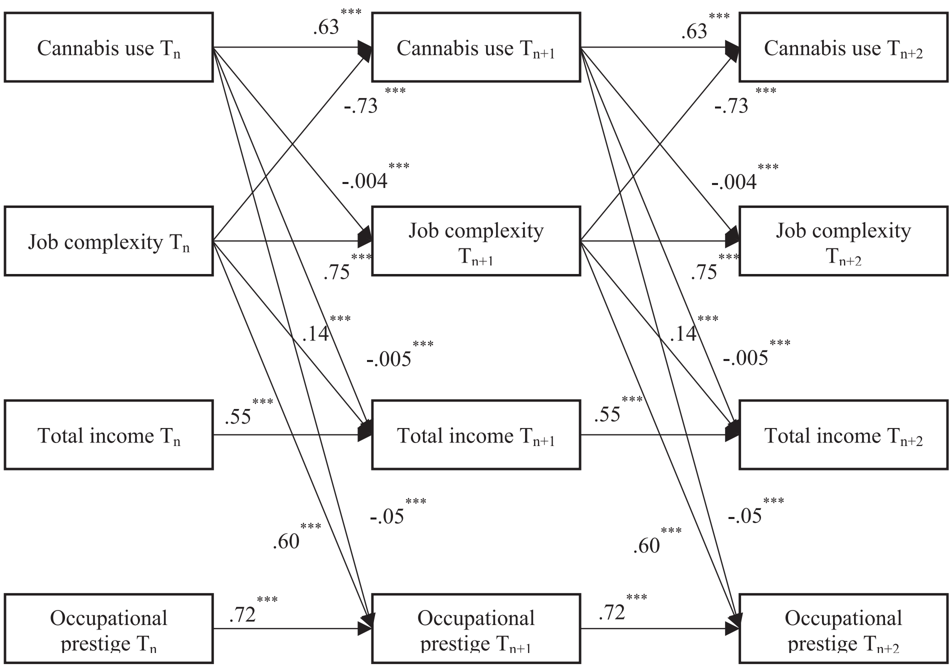

FIGURE 2 | Unstandardized results of hypothesized model. $N=3525$. The figure shows only a basic unit of the model where n ranged from 1 to 6. The relationships among study variables of every three adjacent time points mimic the illustrated model structure. Covariance estimates among variables at the same time point were not illustrated in this figure for parsimony. Total income was natural log transformed. ***$p<0.001$.

TABLE 3 | Results of testing the model indirect effect.

	Indirect effect	Lower 2.5%	Higher 2.5%
1. Cannabis use → Job complexity → Total income	−0.0005	−0.0007	−0.0004
2. Job complexity → Cannabis use → Total income	0.004	0.002	0.006
3. Cannabis use → Job complexity → Occupational prestige	−0.002	−0.004	−0.001
4. Job complexity → Cannabis use → Occupational prestige	0.033	0.019	0.051
5. Relative strengths of 2 over 1	0.003	0.002	0.006
6. Relative strengths of 4 over 3	0.030	0.017	0.048

Note: $N=3525$. Bootstrapping = 5000. Total income was natural log transformed. Across different time points, the R-squared for total income varied from 26.5% to 38.3%, and the R-squared for occupational prestige varied from 38.4% to 59.4%.

5 | Discussion

The increasing consumption of cannabis among employees presents significant challenges for organizational policies and HR practices. However, there is a lack of knowledge regarding its implications in the workplace, prompting the HR Excellence Magazines to issue a call for HR professionals to become "well-versed in the pros and cons of cannabis use for employees and business alike" (HR Excellence Magazines 2023). Our study attempts to advance HR knowledge by examining the implications of cannabis use for employees' long-term extrinsic career outcomes. Our longitudinal results show that cannabis use was negatively and indirectly related to extrinsic career outcomes (i.e., income, occupational prestige) through its negative relationship with job complexity. In addition, our study also shows that job complexity was positively and indirectly related to extrinsic career outcomes through its negative relationship with cannabis use. Importantly, our analysis also indicated that the indirect effect of job complexity to extrinsic career outcomes through cannabis use was stronger than the indirect effect of cannabis use to extrinsic career outcomes through job complexity.

5.1 | Theoretical Implications

Our study contributes to the understanding of the nomological network of cannabis use. Most research on the predictors of cannabis use focuses on socioeconomic factors such as family background, peers, gender, and ethnicity (e.g., Epstein et al. 2015). While some studies consider the impact of employment conditions on cannabis use (e.g., Boden et al. 2017; Hara et al. 2013), such studies tend to focus solely on whether users are employed or unemployed. For example, Hara et al. (2013) showed that workforce participation at the age of 23 was associated with lower cannabis consumption over time, while Teixidó-Compañó et al. (2018) found that individuals who were unemployed used more cannabis than those who were employed. While these findings are informative, they do not account for how the work environment itself, particularly job characteristics, may influence cannabis consumption. Given that most adults spend a substantial portion of their time at work and are impacted directly by the attributes of their jobs, our study extends earlier work by showing that job complexity, an important occupational characteristic, was negatively related to cannabis use, suggesting that employees who perform highly complex jobs are less likely to seek refuge in substance use. Thus, our study fills a critical gap in the literature and shows the value of considering other environmental characteristics that shape employees' substance use. For example, organizational literature often emphasizes the critical role of leadership in influencing employee outcomes, such as motivation and performance. However, to our knowledge, there is no research that examines how leadership might affect employee substance use. It is possible that employees working under abusive supervisors may turn to cannabis as a means to cope (Nandkeolyar et al. 2014). Our study also provides new insights by demonstrating that work characteristics, such as job complexity, can spill over from the work domain into personal space and influence substance use patterns.

Our study also contributes to the understanding of the reciprocal relationship between cannabis use and job complexity in relation to employees' long-term career outcomes. Although cannabis use is often conceptualized as being exogenous to employment outcomes (van Ours 2006), scholars have made important theoretical distinctions between social selection (whereby substance abuse impacts health, education, and employment) and social causation (whereby stressful events, such as unemployment, trigger substance use; Boden et al. 2017). Past research has typically examined these theoretical positions in isolation, but our study suggests that focusing on one at the exclusion of another may produce an incomplete picture of the implications of cannabis use in the workplace, as these two processes are not mutually exclusive (Lynskey and Hall 2000). By testing competing theoretical arguments within the same analytical framework and examining the relative strength of two indirect paths, our study takes an important step towards addressing the theoretical and empirical debates on the role of cannabis in predicting career outcomes (Howard and Osborne 2020). Importantly, our results show that the indirect effect of job complexity on extrinsic career outcomes through cannabis use was significantly stronger than the indirect effect of cannabis use on extrinsic career outcomes through job complexity. Thus, rather than focusing too strongly on cannabis use as a predictor of career outcomes, researchers should also recognize that the nature of jobs themselves may become a potential risk factor for negative career outcomes when such effects are channeled through cannabis use.

Finally, our study addressed several methodological challenges that have hindered the extant literature on cannabis use. First, past research often uses either a cross-sectional design or a time-separation design (whereby one variable was measured at T1 to predict another variable at T2), making it difficult to demonstrate the directional relationship between cannabis use and employment outcomes. In contrast, our study uses longitudinal panel data tested within an auto-regressive cross-lagged model. As Wayne et al. (2022) pointed out, such designs "are the most robust method for assessing directionality because they explicitly incorporate temporal change… and rule out individual difference variables such as personality" (p. 1095). Overall, our design features offer much greater confidence in causal inferences (Ployhart and Vandenberg 2010). Second, unlike past research that often relied on self-reported data from incumbents about their drug use and its effects, leading to same-source bias, we used O*NET data that provides more objective ratings of job complexity and occupational prestige. Third, instead of artificially dichotomizing the variables in the model, we operationalized them as continuous variables based on how they were measured. This allows us to capture more variance in these variables and provide more accurate estimates. Finally, we conducted a series of supplementary analyses to rule out the possibility that our results are influenced by theoretically relevant control variables. We also conducted rigorous endogeneity tests to minimize endogeneity concerns. Taken together, our study makes significant methodological improvements to the existing literature on the work implications of cannabis use.

5.2 | Practical Implications

Our study has a number of implications for human resource management. First, our findings challenge the perception that cannabis use is relatively harmless. As shown in our study, cannabis use can be negatively and indirectly related to extrinsic career outcomes in part due to its effects on the complexity of the user's job. As such, organizational policymakers should continue to use drug-tests to screen job applicants and to deter cannabis use as long as doing so does not violate state laws (e.g., New York). HR departments should also communicate the potential effects of cannabis use with their employees and enact zero-tolerance policies if allowable by state laws. Second, Beverly et al. (2019) suggest that substance use treatment and prevention should adopt a holistic approach by considering environmental variables. One such environmental factor identified in the present research is job complexity. Holistic prevention efforts might include targeting incumbents in low complexity jobs who may require more assistance with vocational need assessment, employment support, and skill development (Henkel 2011). Focusing on job complexity as an intervention strategy may lead to decreased cannabis use, and subsequently, increased income and occupational prestige, thus alleviating the potential financial disadvantages associated with cannabis use. Of course, our study does not imply that low job complexity is inherently undesirable. As an anonymous reviewer aptly pointed out, roles with lower job complexity are vital to the functioning of organizations and societies. Our recommendation is rooted in the premise that intervention can be an effective way to reduce a job incumbent's tendency to rely on cannabis use as a coping mechanism from the stress associated with low complex jobs.

5.3 | Limitations and Future Research

Our study has several limitations that offer avenues for future research. First, although an argument could be made that the 8-year time frame we analyzed lends strength to our findings, it is also possible that a time frame of 8 years may be relatively short given the variables of interest in our study. Participants were in the early stages of their careers during our study period; they were aged between 18 and 24 in the first wave and between 26 and 32 in the last wave. In survey data from the Bureau of Labor

Statistics (2012), 69% of respondents between the ages of 18 and 34 stayed in a job shorter than a year, whereas the percentage dropped to 33% when the respondents were between the ages of 40 and 46. Thus, our study period might be capturing a time when participants were more likely to have less stable careers. Future research should take a life course perspective as the relationship between cannabis use and employment outcomes may have different characteristics over a longer period of time. Second, the use of self-reported cannabis use may lead to questions about the accuracy of the measure. However, Shillington and Clapp (2000) found that self-report agreement was over 80% for lifetime use. Additionally, if self-reported cannabis use was underreported in our data, the results we present may be on the more conservative side (Thompson et al. 2019). Third, as an anonymous reviewer pointed out, although our use of an objective operationalization of job complexity has its merits (as it potentially circumvents same-source bias), objectively rated job complexity may not align with the subjective complexity perceptions of incumbents. Given the archival nature of our study design, we are not able to examine whether study participants' subjective job complexity mirrors objective complexity based on O*NET data (Maynard and Hakel 1997, reported a correlation of 0.34 between an objective and a subjective measure of task complexity). Future research might examine the relative effect of objective and subjective job complexity on cannabis use and career outcomes. Finally, future research should also examine whether major life events may change the relationship between cannabis use and job complexity. For example, although we expected (and found) that lower job complexity may increase the risk of higher cannabis use, this relationship may be attenuated by significant life events such as marriage, the birth of a child, or other changes in family responsibilities that leave people with less time or disposable income that can be allocated to cannabis use. Similarly, although we expected (and found) that lower cannabis use may increase the chance of entering highly complex jobs, this relationship may be attenuated by economic or societal factors such as a recession or the onset of a pandemic.

5.4 | Conclusion

In conclusion, with the legalization of cannabis use and greater consumption of cannabis by employees, HR departments are at a crossroad on how to address this issue in the workplace. Responding to the call to model the bidirectional relationship between cannabis use and employment (Henkel 2011), our study speaks not only to the potential career impact associated with cannabis use but also how this effect is realized. Considering the reciprocal relationship between cannabis use and job complexity on extrinsic career outcomes, our study offers guidance to HR professionals on how to mitigate the potential negative effects of cannabis use.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data are available at Open Science Framework at https://osf.io/4knr3/?view_only=b6535234787b4282857811feb77f0ee2.

Endnotes

[1] While our argument suggests that low job complexity could be a stressor that may cause employees to seek refuge in cannabis, it is also worth considering the possibility that overly complex jobs may tax employees' resource supplies thereby causing them to turn to cannabis to reduce their stress (Liu and Li 2012; also see Pierce and Aguinis 2013 for a discussion of the too-much-of-a-good-thing effect). We tested this possibility in a supplementary analysis.

[2] Cannabis use and job complexity were available in the 2011 wave but income data was not. To keep the same time series structure, we did not include the 2011 wave data in our analysis.

[3] The data is available at Open Science Framework at https://osf.io/4knr3/?view_only=b6535234787b4282857811feb77f0ee2.

[4] Appendix F shows job titles associated with higher (more than 16 days in the last 30 days) and lower (less than 5 days in the last 30 days) cannabis use in 2003 and 2010.

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Appendix A

Endogeneity Analysis

We conducted two sets of analyses to address endogeneity concerns.

First, we used two-stage least squares (2SLS) regression with instrument variables. According to Antonakis et al. (2014a), 2SLS is "a standard practice and probably the most useful and most-used method to ensure consistency of estimates threatened by endogeneity" (p. 1100). To test endogeneity, we employed the Durbin–Wu–Hausman (DWH) test, which compares estimates from ordinary least squares (OLS) with those from 2SLS, with a significant difference of the estimates suggesting that the predictor variable of the model is truly endogenous and the use of 2SLS is appropriate. An ideal instrument should meet two criteria: relevance (the chosen instrument variable should predict the predictor variable of our model) and exclusion (the chosen instrument should have no path to the outcome variable of our model). In essence, the instrument variable is used to obtain a predicted value of the predictor variable of the model in the first stage, and the predicted value is then used to predict the outcome variable of the model in the second stage. As Antonakis et al. (2014b) pointed out, "the instrumental variables purge the endogenous variable from variance that overlaps with the error term" (p. 108).

Accordingly, in the model where cannabis use predicts job complexity, we used cigarette smoking as the instrument variable. Past research has shown the co-consumption of cigarettes and cannabis (Akre et al. 2010), suggesting that "cannabis use is more common among people who smoke cigarettes than among those who do not" (Goodwin et al. 2018, 137), thereby supporting the relevance of the instrument. In contrast, there is no theoretical reason to expect a direct path from cigarette smoking to job complexity because individuals who smoke cigarettes can engage in all types of jobs regardless of their level of complexity (Oldham and Gordon 1999), which suggests that the instrument is exclusive. We operationalized cigarette smoking as the number of days individuals smoked cigarettes over the last 30 days. We also included the control variables (alcohol use, general health status, BMI, annual work hours, age, gender, race, education, family income, and parents' education). We first conducted the DWH test to assess endogeneity of cannabis use. The test rejected the null hypothesis ($\chi^2 = 27.651$, $p < 0.001$), suggesting that cannabis use is endogenous. For the validity of the instrument, it passed both the under-identification test (p-value is less than 0.01) and the weak instrument test (The Cragg-Donald Wald F statistic is above the rule of thumb of 10). The two-stage least squares (2SLS) results are presented below. The second-stage results confirmed that cannabis use negatively predicted job complexity (*estimate* = −0.012, 95% CI = [−0.018, −0.006]) after correcting for any potential endogeneity bias.

In the model where job complexity predicts cannabis use, we used mandatory job training as an instrument. Past research has shown that training requirements were a strong predictor of job complexity (Morgeson and Humphrey 2006). This is particularly so when training is required for reasons related to starting a job, maintaining job skills, or updating the work processes. Theoretically, we do not expect a direct path from required training to cannabis use. We operationalized mandatory job training as participants' enrollment in training because the training was required for the start of a job, skill maintenance and upgrade, and new work processes and methods. We also included all of our control variables listed above. We first conducted the DWH test to assess the endogeneity of job complexity. The test rejected the null hypothesis ($\chi^2 = 6.012$, $p = 0.014$), suggesting that cannabis use is endogenous. For the validity of the instrument variable, it passed both the under-identification test (p-value is less than 0.01) and the weak instrument test (The Cragg-Donald Wald F statistic is above the rule of thumb of 10). The two-stage least squares (2SLS) results are presented below. The second-stage results confirmed that cannabis use negatively predicted job complexity (*estimate* = −5.722, 95% CI = [−11.388, −0.057]) after correcting for any potential endogeneity bias.

To further substantiate our findings, we utilized a three-stage least squares (3SLS) approach to estimate the bidirectional relationship between cannabis use and job complexity simultaneously. The results align with the 2SLS method, indicating that the association between cannabis use and job complexity remains after adjusting for endogeneity.

Second, to further address the issue of selection bias, we conducted two matching approaches—propensity score matching (PSM) and coarsened exact matching (CEM) to identify a potential control condition that is comparable to the treatment condition (Hill et al. 2021; Wang et al. 2024). Both methods aim to create a control group that is similar to the treatment group based on observed covariates. As neither cannabis use nor job complexity was dichotomized, we used individuals who used cannabis over the last 30 days as the treatment condition and those who did not as the control condition, and used individuals who scored above the medium level of job complexity as the treatment condition and those below the medium level as the control condition.

For the PSM approach, we calculated propensity scores for each individual using the control variables as covariates (alcohol use, general health status, BMI, annual work hours, age, gender, race, education, family income, and parents' education). We then matched individuals in the treatment and control groups with similar propensity scores for each variable—cannabis use and job complexity—thereby ensuring a balanced representation of covariates between the groups. For the CEM approach, we first coarsened the continuous or categorical covariates (age, education, family income, parents' education, alcohol use, BMI, general health status, and work hours). We then matched treated individuals with control individuals who shared the same coarsened values for these covariates, as well as the same binary variables (gender and race). Within these two matched samples, we estimated regression models to examine the relationship between cannabis use and job complexity. The results of these analyses are presented below. Comparisons of the treatment with the control conditions across both models (cannabis use predicting job complexity, and job complexity predicting cannabis use) yielded results consistent with our main analysis.

Our endogeneity robustness test did not examine the relationship in the second half of both models (from job complexity to career outcomes and from cannabis use to career outcomes). These relationships have been extensively examined and verified in prior research (e.g., Boden et al. 2017; Boden et al. 2020; Fergusson and Boden 2008; Gonzalez-Mule et al. 2017; Judge et al. 2010).

Results of the Two-Stage/Three-Stage Least Squares Analysis

	First stage		Second stage		First stage		Second stage		Simultaneous equation model (3SLS)			
	Cannabis use		Job complexity		Job complexity		Cannabis use		Job complexity		Cannabis use	
	b	**SE**	***b***	**SE**	***b***	**SE**	***b***	**SE**	***b***	**SE**	***b***	**SE**
Smoking	0.144***	0.004									0.135***	0.007
Mandatory job training					0.131***	0.033			0.122***	0.034		
Cannabis use			−0.012***	0.003					−0.012***	0.003		
Job complexity							−5.722*	2.891			−5.705*	2.848
All control variables	YES		YES		YES		YES		YES		YES	

Note: Total $N = 3525*8 = 28{,}200$. *Smoking* represents the number of days participants smoked over the past 30 days. *Mandatory job training* is training required by the employers for starting a job, skill maintenance and upgrade, and new work processes and methods. The models were estimated using panel data with year fixed effect. *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

Results of the Matching Analysis

	Propensity score matching (PSM)				Coarsened exact matching (CEM)			
	Job complexity (dichotomized)		Cannabis use (dichotomized)		Job complexity (dichotomized)		Cannabis use (dichotomized)	
	b	**SE**	***b***	**SE**	***b***	**SE**	***b***	**SE**
Cannabis use (dichotomized)	−0.039**	0.013			−0.040**	0.013		
Job complexity (dichotomized)			−0.160**	0.006			−0.016**	0.006
N	5082		11,970		4940		10,918	

Note: To identify treatment and control conditions and to enhance the consistency of the reciprocal relationship between cannabis use and job complexity, we dichotomized both variables. We classified individuals who used cannabis over the last 30 days as the treatment condition and those who did not as the control condition. For job complexity, individuals who scored above the median level were designated as the treatment condition, and those below the median level as the control condition. The models were estimated using panel data with year fixed effect. *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

Appendix B

Supplementary Analysis Including Time-Variant Control Variables

	Cannabis use		Job complexity		Total income		Occupational prestige	
	b	**SE**	***b***	**SE**	***b***	**SE**	***b***	**SE**
Study variable								
Cannabis use	0.62***	0.01	−0.004***	0.00	−0.005***	0.00	−0.04***	0.01
Job complexity	−0.63***	0.10	0.74***	0.01	0.11***	0.01	0.48**	0.15
Total income					0.36***	0.02		
Occupational prestige							0.71***	0.01
Control variable								
Alcohol use T1	0.28***	0.04	−0.002	0.00	0.01**	0.00	−0.06	0.03
Alcohol use T2	0.16***	0.03	0.000	0.00	0.01*	0.00	−0.02	0.03
Alcohol use T3	0.15***	0.03	−0.002	0.00	0.01	0.00	−0.02	0.02
Alcohol use T4	0.09**	0.03	0.002	0.00	0.01	0.00	0.04	0.03
Alcohol use T5	0.09**	0.03	0.000	0.00	−0.001	0.00	0.02	0.03
Alcohol use T6	0.12**	0.04	−0.002	0.00	0.01***	0.00	−0.02	0.02
Alcohol use T7	0.03	0.04	0.001	0.00	0.003	0.00	−0.02	0.02
Alcohol use T8	0.06	0.04	0.000	0.00	0.004	0.00	0.00	0.02
Annual work hours T1	0.09	0.29	0.02	0.02	0.90***	0.06	1.13***	0.22
Annual work hours T2	−0.38	0.29	0.05**	0.02	0.58***	0.05	0.71**	0.23
Annual work hours T3	−0.06	0.30	0.02	0.02	0.72***	0.05	0.51*	0.25
Annual work hours T4	0.09	0.34	0.03	0.02	0.75***	0.08	0.67*	0.26
Annual work hours T5	0.06	0.35	0.003	0.02	0.71***	0.08	0.50	0.26
Annual work hours T6	0.07	0.35	0.10***	0.02	0.73***	0.07	1.12***	0.22
Annual work hours T7	−0.83*	0.35	0.07***	0.02	0.75***	0.05	0.92***	0.21
Annual work hours T8	0.15	0.41	0.05***	0.02	0.72***	0.06	0.82***	0.22
Body mass index T1	−0.11**	0.04	−0.001	0.00	0.01*	0.00	−0.02	0.03
Body mass index T2	−0.01	0.04	−0.003	0.00	0.00	0.00	−0.03	0.03
Body mass index T3	−0.07	0.05	−0.002	0.00	0.002	0.00	−0.01	0.03
Body mass index T4	−0.02	0.05	−0.01*	0.00	−0.01	0.01	−0.05	0.03
Body mass index T5	−0.02	0.04	0.000	0.00	−0.001	0.00	−0.02	0.03

	Cannabis use		Job complexity		Total income		Occupational prestige	
	b	**SE**	***b***	**SE**	***b***	**SE**	***b***	**SE**
Body mass index T6	−0.02	0.04	−0.002	0.00	0.004	0.00	0.01	0.03
Body mass index T7	−0.03	0.05	−0.003	0.00	−0.01	0.01	−0.01	0.03
Body mass index T8	−0.06	0.05	−0.002	0.00	−0.003	0.00	−0.01	0.03
General health status T1	−1.23***	0.27	0.05***	0.02	0.10**	0.03	0.50*	0.23
General health status T2	−0.72**	0.27	0.03	0.01	0.01	0.03	0.67**	0.21
General health status T3	−0.30	0.27	0.03*	0.01	0.06*	0.02	0.12	0.20
General health status T4	−0.73*	0.29	0.07***	0.02	0.03	0.03	0.65**	0.21
General health status T5	−0.14	0.29	0.05**	0.02	0.06**	0.02	0.73***	0.20
General health status T6	−0.79**	0.29	0.05**	0.02	0.11***	0.02	0.55**	0.19
General health status T7	−0.66*	0.31	0.05***	0.01	0.06*	0.03	0.29	0.16
General health status T8	−0.95**	0.34	0.04**	0.01	0.05*	0.02	0.32	0.18

Note: $N = 3525$. The effects of time-varying control variables on study variables represent the relationship at the corresponding time point as indicated in each control variable. The effects among study variables are constrained to be equal for variables at T_n predicting variables at T_{n+1}. Total income and annual work hours were natural log transformed. *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

Appendix C

Supplementary Analysis Including Time-Invariant Control Variables

	Cannabis use		Job complexity		Total income		Occupational prestige	
	b	**SE**	***b***	**SE**	***b***	**SE**	***b***	**SE**
Study variable								
Cannabis use	0.63***	0.01	−0.004***	0.001	−0.01***	0.001	−0.05***	0.01
Job complexity	−0.73***	0.10	0.75***	0.01	0.14***	0.01	0.72***	0.01
Total income					0.55***	0.03		
Occupational prestige							0.58***	0.15
Control variable								
Individual age	−0.12	0.16	0.07***	0.01	0.25***	0.02	1.04***	0.14
Individual gender	3.23***	0.50	−0.06*	0.03	0.24***	0.06	−1.69***	0.40
Individual race	−0.42	0.55	−0.03	0.03	0.34***	0.07	1.13**	0.43
Individual education	−1.84***	0.21	0.14***	0.01	−0.02	0.03	1.69***	0.18
Family income	0.12	0.13	0.01	0.01	0.02	0.01	0.05	0.12
Father education	−0.07	0.19	0.003	0.01	−0.02	0.02	0.06	0.14
Mother education	0.40	0.21	0.01	0.01	−0.02	0.02	−0.01	0.15

Note: $N = 3525$. The effect among study variables was constrained to be equal for variables at T_n predicting variables at T_{n+1}. The effects of time-varying control variables were on T1 study variables. Gender was coded as *1 = male* and *0 = female*. Race was coded as *1 = White* and *0 = Other racial groups*. Total income was natural log transformed. Father and mother education was measured with the highest grades completed ranging from 2 to 13 (grades between 13 and 20 were recoded as 13). *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

Appendix D

Multiple-Group Analyses Based on Gender and Race

See Tables D1 and D2.

TABLE D1 | Gender difference in hypothesized model results.

	Cannabis use		Job complexity		Total income		Occupational prestige	
	b	**SE**	***b***	**SE**	***b***	**SE**	***b***	**SE**
Male (N = 1982)								
Cannabis use	0.62***	0.01	−0.003***	0.00	−0.006***	0.00	−0.04***	0.01
Job complexity	−0.70***	0.15	0.76***	0.01	0.15***	0.02	0.67***	0.19
Total income					0.53***	0.04		
Occupational prestige							0.71***	0.01
Female (N = 1543)								
Cannabis use	0.62***	0.02	−0.005***	0.00	−0.006**	0.00	−0.06***	0.01
Job complexity	−0.64***	0.13	0.75***	0.01	0.14***	0.02	0.49*	0.25
Total income					0.56***	0.03		
Occupational prestige							0.72***	0.02
Relative strength								
Cannabis use	—	—	0.002	0.00	0.000	0.00	0.02	0.02
Job complexity	−0.06	0.20	—	—	0.003	0.02	0.17	0.31
Total income					—	—	—	—
Occupational prestige					—	—	—	—

Note: Total N = 3525. Model fit: χ^2 = 2733.273, df = 960, RMSEA [90% CI] = 0.032 [0.031, 0.034], CFI = 0.931, TLI = 0.930. Relative strengths indicate the effect of the same underlying relationship of study variables for male over female. Total income was natural log transformed. * $p < 0.05$. ** $p < 0.01$. *** $p < 0.001$.

TABLE D2 | Race difference in hypothesized model results.

	Cannabis use		Job complexity		Total income		Occupational prestige	
	b	**SE**	***b***	**SE**	***b***	**SE**	***b***	**SE**
White (N = 2142)								
Cannabis use	0.64***	0.01	−0.004***	0.00	−0.004**	0.00	−0.05***	0.01
Job complexity	−0.67***	0.12	0.75***	0.01	0.12***	0.01	0.37*	0.18
Total income					0.55***	0.03		
Occupational prestige							0.73***	0.02
Other races (N = 1355)								
Cannabis use	0.61***	0.02	−0.002**	0.00	−0.007**	0.00	−0.03**	0.01
Job complexity	−0.71***	0.18	0.76***	0.01	0.17***	0.02	0.96***	0.26
Total income					0.53***	0.05		
Occupational prestige							0.69***	0.02
Relative strength								
Cannabis use	—	—	−0.002	0.00	0.003	0.00	−0.02	0.02
Job complexity	0.04	0.21	—	—	−0.05*	0.03	−0.59	0.31
Total income					—	—	—	—
Occupational prestige					—	—	—	—

Note: Total N = 3497. Model fit: χ^2 = 2707.821, df = 960, RMSEA [90% CI] = 0.032 [0.031, 0.034], CFI = 0.931, TLI = 0.930. Relative strengths indicate the effect of the same underlying relationship of study variables for White over Other races. Though the impact of job complexity on total income was significantly different between the White group and Other races, there was no significant difference in the indirect effect of cannabis use on total income via job complexity. Total income was natural log transformed. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Appendix E

Supplementary Analysis Examining School Enrollment Status

See Tables E1 and E2.

TABLE E1 | Modeling results controlling time-varying school enrollment.

	Cannabis use		Job complexity		Total income		Occupational prestige	
	b	**SE**	***b***	**SE**	***b***	**SE**	***b***	**SE**
Study variable								
Cannabis use	0.63***	0.01	−0.004***	0.00	−0.01***	0.00	−0.05***	0.01
Job complexity	−0.67***	0.10	0.75***	0.01	0.15***	0.01	0.55***	0.15
Total income					0.54***	0.03		
Occupational prestige							0.72***	0.01
Control variable								
School enrollment T1	−3.61***	0.50	0.19***	0.03	−0.54***	0.07	2.18***	0.44
School enrollment T2	−0.77	0.49	0.02	0.03	−0.21***	0.05	−0.14	0.42
School enrollment T3	−1.25*	0.51	0.08*	0.03	−0.34***	0.05	0.65	0.44
School enrollment T4	−1.67**	0.55	0.20***	0.04	−0.28***	0.07	2.14***	0.51
School enrollment T5	−1.99**	0.61	0.24***	0.04	−0.24***	0.06	2.36***	0.53
School enrollment T6	−1.97**	0.65	0.06	0.04	−0.16*	0.06	0.46	0.60
School enrollment T7	−0.94	0.73	0.11*	0.04	−0.21**	0.07	0.45	0.53
School enrollment T8	−0.35	0.87	0.10*	0.04	−0.14*	0.06	0.60	0.51

Note: $N = 3525$. Model fit: $\chi^2 = 2978.685$, df = 704, RMSEA [90% CI] = 0.030 [0.029, 0.031], CFI = 0.923, TLI = 0.918. School enrollment was coded as *0 = not enrolled* and *1 = enrolled*. The effect of time-varying school enrollment on study variables represents the relationship at the corresponding time point as indicated in each control variable. The effect among study variables was constrained to be equal for variables at T_n predicting variables at T_{n+1}. Total income was natural log transformed. *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

TABLE E2 | Modeling results with recoded work-related data.

	Cannabis use		Job complexity		Total income		Occupational prestige	
	b	**SE**	***b***	**SE**	***b***	**SE**	***b***	**SE**
Study variable								
Cannabis use	0.63***	0.01	−0.004***	0.00	−0.01***	0.00	−0.05***	0.01
Job complexity	−0.80***	0.11	0.80***	0.01	0.17***	0.01	1.00***	0.16
Total income					0.52***	0.03		
Occupational prestige							0.72***	0.01

Note: $N = 3512$. Each wave's data on job complexity, total income, and occupational prestige were recoded as missing if individuals were enrolled in school in that wave. Model fit: $\chi^2 = 1858.014$, df = 480, RMSEA [90% CI] = 0.029 [0.027, 0.030], CFI = 0.932, TLI = 0.930. The effects among study variables were constrained to be equal for variables at T_n predicting variables at T_{n+1}. Total income was natural log transformed. ***$p < 0.001$.

Appendix F

Cannabis Use by Occupation

Year	Occupational code	Number of days used marijuana in the last 30 days	Sample size	Job title
2010	8810	27.50	4	Painting workers
	7620	25.00	3	Other installation, maintenance, repair workers
	8030	23.00	4	Machinists
	1110	21.00	4	Network systems and data communicatinalysts
	4520	20.67	3	Miscellaneous personal appearance workers
	5100	20.29	7	Bill and account collectors
	8740	20.00	6	Inspectors, testers, sorters, samplers, and weighers
	6200	19.67	3	First-line supervisors/managers of construction trades and extraction workers
	5310	19.33	3	Interviewers, except eligibility and loan
	4140	19.00	3	Dishwashers
	6260	18.82	17	Construction laborers
	4010	18.22	9	First-line supervisors of food preparation and serving workers
	2600	17.67	3	Artists and related workers
	4610	17.64	14	Personal and home care aides
	4020	17.48	23	Cooks
	2750	17.33	3	Musicians, singers, and related workers
	4220	17.31	13	Janitors and building cleaners
	7200	17.23	13	Automotive service technicians and mechanics
	4710	17.14	7	First-line supervisors of non-retail sales
	20	16.90	10	General and operations managers
	7750	16.36	11	Miscellaneous assemblers and fabricators
	4650	16.33	3	Personal care and service workers, all other
	4800	4.67	3	Advertising sales agents
	5930	3.91	11	Office and administrative support workers, all other
	6420	3.33	3	Painters, construction and maintenance
	730	3.00	3	Other business operations specialists
	540	2.33	3	Claims adjusters, appraisers, examiners, and investigators
	4960	2.20	5	Sales and related workers, all other
	3410	2.00	4	Health diagnosing and treating practitioner support technicians
	4430	2.00	3	Miscellaneous entertainment attendants and related workers
	5840	2.00	4	Insurance claims and policy processing clerks
	800	1.33	6	Accountants and auditors
	5160	1.00	3	Tellers
	2850	0.67	3	Writers and authors
	4920	0.67	3	Real estate brokers and sales agents
	2010	0.25	4	Social workers
	1040	0.17	6	Computer support specialists
	3240	0.00	4	Therapists, all other
	7700	0.00	4	First-line supervisors of production and operating workers

Year	Occupational code	Number of days used marijuana in the last 30 days	Sample size	Job title
2003	8740	22.00	6	Inspectors, testers, sorters, samplers, and weighers
	4130	21.69	13	Dining room and cafeteria attendants and bartender helpers
	4710	21.25	4	First-line supervisors/managers of non-retail sales workers
	4530	21.00	3	Baggage porters, bellhops, and concierges
	7620	20.80	5	Other installation, maintenance, and repair workers
	8140	20.33	3	Welding, soldering, and brazing workers
	5630	20.33	3	Weighers, measurers, checkers, and samplers, recordkeeping
	2920	18.67	3	Television, video, and motion picture camera operators and editors
	6330	18.33	3	Drywall installers, ceiling tile installers, and tapers
	4520	18.33	3	Miscellaneous personal appearance workers
	9360	18.29	7	Service station attendants
	9350	18.25	4	Parking lot attendants
	9600	17.13	8	Industrial truck and tractor operators
	8320	17.00	3	Sewing machine operators
	8220	16.67	3	Metalworkers and plastic workers, all other
	4230	16.30	10	Maids and housekeeping cleaners
	7810	16.25	4	Butchers and other meat, poultry, and fish processing workers
	4140	4.89	9	Dishwashers
	7310	4.67	3	Heating, air conditioning, and refrigeration mechanics and installers
	5840	4.40	5	Insurance claims and policy processing clerks
	2340	4.38	16	Other teachers and Instructors
	4420	4.33	3	Ushers, lobby attendants, and ticket takers
	3520	4.00	3	Opticians, dispensing
	3950	3.33	3	Lifeguards and other protective service workers
	4060	2.88	8	Counter attendant, cafeteria, food concession, and coffee shop
	4740	2.80	5	Counter and rental clerks
	20	2.67	3	General and operations managers
	2910	2.00	4	Photographers
	5930	1.67	3	Office and administrative support workers, all other
	9720	1.67	3	Refuse and recyclable material collectors
	4810	1.50	4	Insurance sales agents
	2310	1.38	8	Elementary and middle school teachers
	410	1.00	3	Property, real estate, and community association managers
	1960	1.00	3	Other life, physical, and social science technicians
	3800	1.00	3	Bailiffs, correctional officers, and jailers
	6520	1.00	3	Sheet metal workers
	1000	0.33	3	Computer scientists and systems analysts

Note: For ease of interpretation, we restricted this summary to jobs in which the sample size was at least 3 (i.e., there were at least three respondents for that job code/title). The number of days used cannabis in the last 30 days was an average of the incumbents' reports.