1-24-2024

Correlates for Nonmedical Prescription Opioid Use Among Young Adults

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This is to certify that the doctoral dissertation by

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Walden University
2024

Abstract

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Uchenna Sam Chinweuba

MPH, American Public University, 2019

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Dissertation Submitted in Partial Fulfillment

of the Requirements for the Degree of

Doctor of Philosophy

Public Health

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February 2024

Abstract

Opioid misuse is a global burden that needs a critical solution to reduce the prevalence rate among young adults aged 18 to 25. Scholarly literature lacked studies on the precise individual-level factors and sociobehavioral level of influence as key determinants of nonmedical prescription opioid use (NMPOU) among young adults aged 18 to 25 years, which were required to improve safeguards against nonmedical prescription opioid misuse and addiction. The purpose of this quantitative correlational study of a cross-sectional nature was to determine the predictive relationship between attitudes, perceived norms, personal agency, and nonmedical prescription opioids among young adults while controlling for age, gender, and educational level. The integrated behavior model was the theoretical framework used to evaluate the sociobehavioral level of influence. A purposeful convenience sampling method was used for the recruitment of 188 university students aged 18 to 25 years, and data were collected using an anonymous online survey. The results of the multiple linear regression showed that perceived norms had a significant correlation, $F(3,184) = 8.164$, $p = .035$, *and* $R^2 = .117$. Educational level had a significant correlation, $F(2, 185) = 9.805$, $p = .005$, $R^2 = .096$. Gender had a significant correlation, $F(1, 186) = 13.491$, $p = .003$, $R^2 = .086$. Attitudes ($p = .119$) and personal agency ($p = .108$) did not show any statistical significances. Hence, null hypotheses were not rejected. The social change implication for this study and its findings provide significant insights for community leaders, policymakers, university administrators, and policy makers as they strive to implement a variety of effective health behavior programs and policies related to opioid misuse activities within campuses and communities.

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Dedication

I dedicated this dissertation to Almighty God, my parents Chief Elder Samuel A. Chinweuba (JP) and Mrs Ngozi C. Chinweuba, my wife Lady Obiageli E. Chinweuba, my children Chiagoziem, Chijiobim, and Chimkasimma, for their prayers, love, support, patience, and encouragement throughout the entire doctoral study.

Acknowledgments

First, I express my gratitude to the Almighty God for the invaluable direction, wisdom, knowledge, strength, and resilience bestowed upon me during this PhD study. I express my sincere gratitude to Dr. Patrick Dunn, my exceptional committee chair, for his exemplary mentorship. I appreciate the timely, detailed, constructive, and valuable edits and feedback that consistently guided me in the right direction when I felt uncertain. Furthermore, I am grateful for his patient guidance throughout the entire dissertation process. You provided me with motivation and instilled in me a sense of optimism that I could successfully accomplish my objective of finishing my dissertation. I deeply value the invaluable insights I have gained from you; your unwavering dedication, mentoring approach, and diligence inspire me to consistently pursue excellence and become a compassionate mentor to others as well. I would like to express my immense gratitude to my second committee member, Dr. Shuey Schumaker, for always ensuring meticulous attention to detail and the successful completion of a high-quality quantitative research study. I appreciate your involvement and assistance during the course work and dissertation process. I would like to express my gratitude to Dr. Loretta Shields, my university research reviewer (URR), for her invaluable support and prompt input in assisting me to structure and articulate material effectively. I am grateful to University A in Nigeria for consenting for this study. I express my genuine gratitude to the entire Walden management team, faculty, and support team. To my parents, spouse, children, siblings, nephews, and nieces, I thank you all for your unwavering presence in my life. To my classmates, I wish you all the best and God bless us in all our future endeavors.

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Chapter 1: Foundation to the Study

Globally, people are becoming more concerned about young people using opioids for purposes other than medical treatment and passing away from overdoses (Columbia University Mailman School of Public Health, 2017). Nonmedical prescription opioid use (NMPOU) is when an opioid is used in a way or dose that is not prescribed, when someone uses another person's prescription opioid, even if it is for a valid medical cause, or when an opioid is used just for the sensation it gives off (Papazisis et al., 2018).

Previous studies on NMPOU in Nigeria showed that one in seven persons aged 15 to 64 years had used a drug other than tobacco and alcohol in 2018, while the annual prevalence showed that more men are drug users at 21.8% or 10.8 million compared to women at 7.0% or 3.4 million in Nigeria (United Nations Office on Drugs and Crime [UNODC], 2018). Since 1999, the number of opioid-related deaths has tripled, and in 2017, over 72,000 Americans, including teenagers and young adults between the ages of 15 and 24, died because of opioid abuse (Hudgins et al., 2019; National Institute on Drug Abuse [NIDA], 2018).

According to research results published in an article that appeared in the *Journal of the World Psychiatric Association*, the rate of overdose deaths from prescription opioid misuse among teenagers and young adults worldwide has increased noticeably, surpassing a 200% increase in overdose deaths from opioid use between the years 2000 and 2014 by about 550% based on different countries and periods (Martins & Ghandour, 2017).

In the United States, there has been an unusual rise in prescription opioid abuse and addiction and difficulties caused by alcoholism, drug abuse, and substance use disorders. These issues hurt people's productivity and health, burdening their families, friends, and communities (Substance Abuse Mental Health Service Administration, 2013). My study focused extensively on the most common opioids among young adults in Nigeria between 18 and 25. These drugs are categorized as natural (morphine and codeine), semi-synthetic (hydrocodone, oxycodone, heroin, and hydromorphone), synthetic (fentanyl and tramadol), and endogenous (methadone; UNODC, 2019).

Problem Statement

One in seven Nigerians between the ages of 15 and 64 has a history of substance abuse unrelated to smoking or drinking, according to studies on NMPOU and other substance misuse in 2018 (UNODC, 2018). Young adults' substance abuse, particularly the unlawful use of prescription opioids, with apparent lack of concern for the consequences for their health or the larger community, is on the rise in Nigeria (UNODC, 2018). The term *substance use* encompasses the consumption or absorption of many substances, such as alcohol, tobacco products, narcotics, inhalants, and other chemicals that can be ingested, inhaled, injected, or otherwise taken into the body which can potentially lead to dependence and cause harmful effects (Centers for Disease Control and Prevention [CDC], 2023). *Substance use* can involve any chemical substance, other than one found in food, that, when ingested or administered intravenously, alters aspects of mental health such emotions, mood, reasoning, behaving, and consciousness (World Health Organization, 2022). The inappropriate use of a psychoactive chemical or drug by a person that results in social, physical, academic, occupational, and mental health impairments is known as *substance abuse* (Jahan & Burgess, 2022).

According to the annual prevalence of illegal drug users in Nigeria, 10.8 million or 21.8% of males and 3.4 million or 7.0% of women are frequent drug users (UNODC, 2018). More than 12% of deaths in 2016 were linked to opioid overdoses among teenagers and young people aged 15 to 24 (UNODC, 2018). There has been a 4-fold increase since 2001, leading to a public health catastrophe in the United States (Gomes et al., 2018). The National Survey on Drug Use and Health recruited 27,857 adolescents (12–17 years old) and 28,213 young adults (18–25 years old) for the years 2015 and 2016 retrospective analysis to investigate the prevalence of NMPOU, opioid misuse, opioid use disorder, and other substance abuse. It was found that more female than male respondents were more likely to initiate some prescription opioids (30.3% versus 24.8%, respectively; Center for Behavioral Health Statistics, 2017). In Nigeria, drug use, including the use of prescribed opioids for both medical and nonmedical purposes, is notably higher than the global yearly prevalence of drug use among young adults, which was 5.6% in 2016. (UNODC, 2019). Studies have shown that university/college students are more likely to share and store prescriptions, particularly opioids, unsafely, increasing the likelihood of prescription misuse (Johnston et al., 2014; McCabe, 2008; Weyandt et al., 2021). The rise in opioid abuse among university/college students has been a public health concern (Keyes et al., 2014). As a result, more research is needed on NMPOU among university students, hence the impetus for this study.

Purpose of the Study

I quantitatively examined the predictive relationship between the three constructs of the integrated behavior model (IBM), demographic factors (age, gender, educational level) as significant determinants of NMPOU among young adults in Nigeria. Each of the three primary constructs in this study have subconstructs, including (a) attitude, which has two subconstructs known as instrumental attitude (i.e., perceived benefits) and experiential attitude (i.e., perceived feelings); (b) perceived norms, which has three subconstructs known as the descriptive norm (i.e., perception of the typical behavior of other people), subjective norm (i.e., perception about whether significant people or a group of people will accept, disapprove, and support a particular behavior) and injunctive norm (i.e., perception of what other people think should be done); and (c) personal agency, which has two subconstructs known as self-efficacy (i.e., confidence in executing a behavior) and perceived behavior control (i.e., perceived difficulty or ease in executing the behavior; Fishbein, 2000; Fishbein et al., 2002; LaMorte, 2022).

Self-efficacy refers to a person’s confidence level in their ability to perform the behavior in the face of various obstacles or challenges (Glanz et al., 2015). Perceived control refers to the perceived degree of control over behavioral performance, which can be determined by a person’s perceptions of the degree of various environmental factors that make it easier or more complex to perform the behavior (Glanz et al., 2015).

Research Questions and Hypotheses

The following research questions for the study were helpful in developing interventions that lessen the effects of NMPOU among young adults aged 18 to 25 using the three constructs of the IBM (i.e., attitudes, perceived norms, and personal agency) to evaluate the predictive relationship among all variables.

RQ1: Is there an association between attitudes (instrumental and experiential) and nonmedical prescription opioid use, controlling for age, gender, and educational level?

$H_0$1: There is no relationship between attitudes (instrumental and experiential) and nonmedical prescription opioid use, controlling for age, gender, and educational level.

H_a1: There is a relationship between attitudes (instrumental and experiential) and nonmedical prescription opioid use, controlling for age, gender, and educational level.

RQ2: Is there an association between perceived norms (descriptive, subjective, and injunctive) and nonmedical prescription opioid use, controlling for age, gender, and educational level?

$H_0$2: There is no relationship between perceived norms (descriptive, subjective, and injunctive) and nonmedical prescription opioid use, controlling for age, gender, and educational level.

H_a2: There is a relationship between perceived norms (descriptive, subjective, and injunctive) and nonmedical prescription opioid use, controlling for age, gender, and educational level.

RQ3: Is there an association between personal agency (perceived control and self-efficacy) and nonmedical prescription opioid use, controlling for age, gender, and educational level?

$H_0$3: There is no relationship between personal agency (perceived control and self-efficacy) and nonmedical prescription opioid use, controlling for age, gender, and educational level.

H_a3: There is a relationship between personal agency (perceived control and self-efficacy) and nonmedical prescription opioid use, controlling for age, gender, and educational level.

The study variables were as follows:

- Attitude is a categorical variable measured on an ordinal scale using five Likert scale responses (5 = *strongly agree* to 1 = *strongly disagree*) to answer the corresponding questionnaires.
- Perceived norm is a categorical variable measured on an ordinal scale using five Likert scale responses (5 = *strongly agree* to 1 = *strongly disagree*) to answer the corresponding questionnaires.
- Personal agency is a categorical variable measured on an ordinal scale using five Likert scale responses (5 = *strongly agree* to 1 = *strongly disagree*) to answer the corresponding questionnaires.
- Nonmedical prescription opioid use is a dependent variable measured as the frequency of use (continuous) on an interval scale.

Research Gap

Although several researchers have investigated the issue of nonmedical prescription opioid use, opioid misuse, opioid addiction, and related risk behavior, studies have not examined individual-level correlates affecting the prevalence, morbidity, and mortality rates for nonmedical prescription opioid use among young adults in Nigeria. These correlates include attitude, perceived norms (injunctive, subjective, and descriptive), and personal agency (perceived control and self-efficacy). There is overwhelming evidence that research that applies explicit theoretical models for behavioral interventions is more successful at using behavioral intervention approaches than research with no theoretical underpinnings (Alemayehu et al., 2021).

The dependent variable in this study is nonmedical prescription opioid use, and the three constructs of the IBM (attitudes, perceived norms, and personal agency) are the independent variables. The controlling variables are age, gender, and education, which helped to determine an in-depth correlation among the variables. This research can assist future researchers in better understanding the factors influencing nonmedical prescription opioid use among young adults in Nigeria between 18 and 25. The findings provided a better framework to create effective policies and laws that monitor medical and nonmedical prescription opioids by healthcare providers, prevent people from accessing nonmedical prescription opioids from street vendors, and thereby prevent opioid addiction in Nigeria.

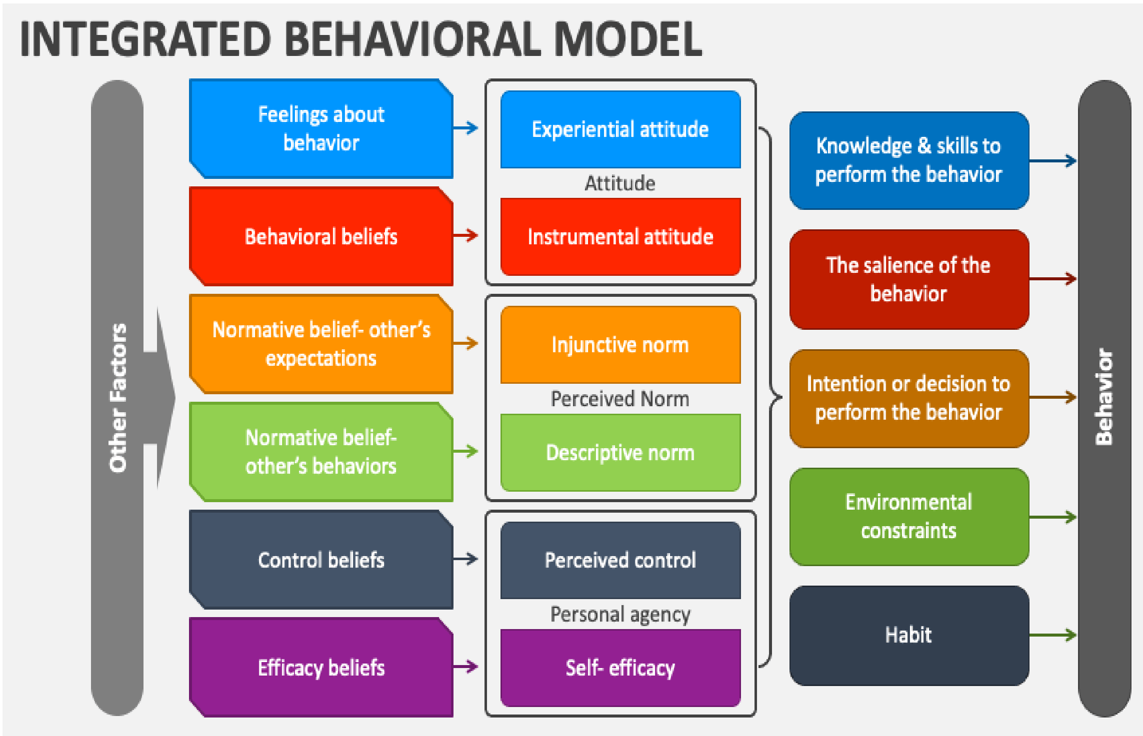
Theoretical Foundations for the Study

Researchers' investigations into health behaviors revealed that people's views and beliefs affect whether they carry out a particular health-related action. The life-course theory (Elder, 1998), the extended parallel process model (Witte, 1992), the social cognitive theory (Bandura, 1969), the health belief model (Rosenstock et al., 1988), and the theory of planned behavior have been used by researchers (Ajzen, 1991). These theories can predict future behavior change in an individual and provide intervention strategies to lessen and control health behavior change. Scholars have used these theories to assess individual-level factors influencing substance use, including nonmedical prescription opioid use among young adults.

Fishbein's IBM (see Figure 1) served as a behavioral framework for the study. The nature of my study has been widely used in public health research by other researchers to predict health behaviors, such as mood, emotions, attitudes, perceived intentions, and perceived behavior control, behind health problems, recognizing and affecting human behavior (The Behavior Institute, n.d.). Fishbein's IBM is the foundation for this study's hypotheses and concepts. For example, Fishbein (2000) used the three IBM constructs to determine whether a person has an intense desire to engage in a specific behavior, urgent skills, and constrained environmental restrictions. Likewise, the critical determinants of health behavior, such as attitudes toward behavior, perceived ability to perform the behavior, and perceived norms of the behavior, can be determined by a person's behavior and intentions, according to Fishbein et al.'s (2002) analysis of the commonalities among these theories.

Figure 1

Fishbein's Integrated Behavior Model



Note. From *Integrated Behavioral Model* by Collidu.com, n.d. (https://www.collidu.com/presentation-integrated-behavioral-model).

According to the IBM, if an individual has a solid intention to perform a behavior, the necessary skills, and limited environmental constraints, there is a high likelihood that the individual will perform the behavior (Fishbein et al., 2002). This framework emphasized the role of attitudes (instrumental and experiential), perceived norms (descriptive, subjective, and injunctive), and personal agency (perceived control and self-efficacy) towards a given behavior (The Behavior Institute, n.d.).

The IBM constructs—attitude (instrumental and experiential), perceived norm (descriptive, subjective, and injunctive), and personal agency (perceived confidence and behavioral control)—are shown in this model to be the main factors influencing whether someone will engage in the behavior (The Behavior Institute, n.d.). The three IBM components were employed in my study to detect and predict intents, feelings, and moods related to nonmedical prescription opioid usage among young individuals in Nigeria between the ages of 18 and 25.

This framework offers effective behavior modification and intervention techniques for lowering opioid abuse disorders, physical injuries, and the financial constraints of young adults' opioid misuse and addiction.

Nature of the Study

To answer the research questions, I selected a quantitative primary data design. A quantitative cross-sectional design aimed to investigate the relationship between dependent and independent variables. The independent variables are the three IBM constructs of (a) attitude (experiential and instrumental), (b) perceived norms (injunctive, subjective, and descriptive), and (c) personal agency (perceived control and self-efficacy), and the dependent variable is nonmedical prescription opioid use, with age, gender, and education as controlling variables.

Primary data is the original information directly retrieved by researchers from the designated participants via self-administered questionnaires, interviews (telephone or face-to-face), and surveys (Prada-Ramallal et al., 2018). Primary data analyses provide firsthand information about any correlation between the dependent and independent variables, as well as a foundation for future studies and potential expansion by future researchers (Ajayi, 2017; Prada-Ramallal et al., 2018). This study was descriptive with a cross-sectional design that examines the prevalence rate, morbidity, and mortality of nonmedical prescription opioid use using IBM constructs to answer the hypotheses of the three research questions (see Wang & Cheng, 2020).

The cross-sectional design is a type of descriptive study in which data are collected based on the presence or level of one or more variables of interest (health-related conditions), whether exposure (risk factor) or outcome (disease), that exist among the designated population at a given time (Aggarwal & Ranganathan, 2019). The findings of this quantitative study promote positive social change by assessing key correlates with nonmedical prescription opioid use among young adults (aged 18 to 25 years) in Nigeria.

Definitions

Attitude is a strong desire to engage in a particular behavior (The Behavior Institute, n.d.). I employed the Likert scale (bipolar type) to measure attitude subconstructs. A bipolar Likert scale is used when a researcher wants respondents to respond strongly positively or negatively (Qualtrics, 2023). I used a 5-point Likert scale measurement of respondents' intention to engage in nonmedical prescription opioid use to determine correlation coefficients and the degree of prediction based on the model construct questionnaires.

Morbidity is symptomatic or unhealthy for a disease or condition (Hernandez & Kim, 2022). The morbidity rate is the frequency with which a disease or illness occurs in a population and can be used to assess a population's health and healthcare needs. Infections can range from acute to chronic and long-term (Hernandez & Kim, 2022).

Monoculturalism is the presence of a single ethnic group within a territory or society that supports, advocates, and allows the expression of a single culture (Hunt, 2020)

Mortality is the state of being mortal or confirmed to die (National Cancer Institute, n.d.). In medicine, the mortality rate refers to the number of deaths in a specific group over a given period (National Cancer Institute, n.d.). Mortality may be reported for people with a particular disease who live in a specific area of the country or are of a particular gender, age, or ethnic group (National Cancer Institute, n.d.). This can be measured by the estimated total number of deaths in a population of a given sex and/or age, divided by the total number of this population expressed per 100,000 population for a given year, in each country, territory, or geographic area (National Cancer Institute, n.d.).

Multiculturalism refers to the presence of multiple ethnic and cultural groups within a society (Clayton, 2020; Ivison, 2015).

Nonmedical prescription opioid use (NMPOU) is the act of taking an opioid in a way or dose that is not prescribed, taking someone else's prescription opioid, even if for a legitimate medical reason, or taking a prescription opioid for the pleasure it provides (Papazisis et al., 2018).

Opioids are a drug class that includes heroin, synthetic opioids like fentanyl, and prescription pain relievers like oxycodone (OxyContin®), hydrocodone (Vicodin®), codeine, morphine, tramadol, and many others (NIDA, n.d.).

Opioid use disorder is the chronic use of opioids that causes clinically significant distress or impairment (Dydyk et al., 2022).

Perceived control refers to the perceived degree of control over behavioral performance, which can be determined by a person's perceptions of the degree of various environmental factors that make the behavior more accessible or more challenging to perform (Glanz et al., 2015).

Prevalence is a statistical concept that refers to the number of disease cases in a specific population at a given time. In contrast, incidence refers to the number of new cases that develop in a specific period (National Institute of Mental Health, n.d.).

Self-efficacy refers to a person's belief in their ability to perform a behavior despite various obstacles or challenges (Glanz et al., 2015).

Substance abuse is the inappropriate use of a psychoactive chemical or drug by a person that causes social, physical, academic, occupational, and mental health impairments (Jahan & Burgess, 2022).

A university student refers to a student in higher education who is pursuing various qualifications (Bennett & Holloway, 2014).

Assumptions

According to recent literature review and findings on the abuse of nonmedical prescription opioid use, it was assumed that many university students in Nigeria between the ages of 18 and 25 (both genders) are vulnerable and at risk, because they are more likely to react negatively to stress related to their studies, interact with their peers, and be curious about trying new things. Therefore, this study has numerous assumptions based on demographic factors and IBM constructs used to investigate correlates for nonmedical prescription opioid use, which are analyzed using an anonymous online self-reported survey, descriptive statistics, and multiple linear regression.

First, I assumed that demographic characteristics (age, gender, educational level) would have a robust predictive association with nonmedical prescription opioid use among young adults aged 18 to 25 years. As a result, the expected responses of participants in the online self-reported survey about their current and past experiences with opioid use for nonmedical purposes addressed this assumption.

Second, I assumed that university students aged 18 to 25 years are more prone and vulnerable to nonmedical opioid misuse due to negative attitudes, lower levels of perceived norms, and lower levels of personal agency.

Third, I assumed that an individual could assess a behavior of interest and still perform the behavior regardless of whether the effect is positive or negative. Therefore, I examined how an individual's attitude correlates with the intention to perform behavior.

Fourth, I assumed that if young adults report a more positive attitude toward nonmedical prescription opioid use, they are less likely to quit.

Fifth, I assumed that the stronger the desire to perform the behavior, the more likely it will be successfully performed. Therefore, this study investigated how an individual's perceived norm directly correlates with nonmedical prescription opioid use.

Sixth, I assumed that a person could acquire the opportunities and resources needed to successfully perform a desired behavior regardless of the person's intention.

Hence, I examined the correlation between respondents' perceived control and respondents' intention to engage in the behavior.

Scope and Delimitations

My study adopted a cross-sectional approach in analyzing primary data collection quantitatively. Primary data was collected via an anonymous online survey from university students in Nigeria between the ages of 18 and 25. The data examined the associations between demographic variables (age, gender, educational level), nonmedical prescription opioid use, and the IBM constructs (attitude, perceived norms, and personal agency) among young adults in Nigeria between the ages of 18 and 25.

Due to the personal and sensitive nature of the study, an anonymous online self-administered surveys were used for data collection, obviating the requirement for in-person or telephone interviews and ensuring the confidentiality of personal information throughout the data-gathering process. Therefore, the main delimitation for this study was the use of online self-administered surveys, which may contribute to skewed results due to multiculturalism characteristics within the suggested university samples.

Generalizability and Limitations

Convenience sampling presents still another generalizability problem, as some survey respondents can decide not to respond to certain questions out of concern for potential legal repercussions leading to information bias (Althubaiti, 2016; John, 2021). Nigeria is a multicultural country with various ethnic and cultural groupings. Therefore, this study's findings can be generalized to other populations and environments with demographics comparable to those of Nigeria (Frankfort-Nachmias et al., 2015).

Significance

This study broadly emphasized the behavioral correlation between nonmedical opioid prescription use among young adults (18 to 25 years old). In addition, future researchers may benefit from the study by understanding the patterns and trends in the descriptive and predictive relationships between the IBM constructs, demographic variables (age, gender, and educational level), and nonmedical prescription opioid use among university students.

My study offered a robust framework for Nigerian universities to address the issues of opioid addiction and opioid misuse among students, which significantly negatively impact their academic performance. Furthermore, this study outcome provided a new strategy to the existing opioid intervention program on campus by providing further opioid management insight and improving university students' sociobehavioral values.

Summary

Opioids are a class of drugs with a high propensity for addiction that are used to treat various types of pain (Hoffman et al., 2019). Nonmedical prescription opioid use (NMPOU) is when an opioid is used in a way or dose that is not recommended, when someone uses another person's prescription opioid, even if it is for a valid medical cause, or when an opioid is used for the feeling, it generates (Papazisis et al., 2018). In Nigeria, previous studies on nonmedical prescription opioid use found that one in seven people aged 15 to 64 had used drugs other than tobacco and alcohol in 2018 (UNODC, 2018). The goal of this quantitative cross-sectional correlational study was to identify the predictive relationships between independent variables (attitudes, perceived norms, and personal agency), demographic covariates (age, gender, and educational level), and nonmedical prescription opioid use (dependent variable) among young adults aged 18 to 25 years.

The IBM was the study's theoretical framework used to assess the attitude, intentions, self-control, and sociobehavioral level of effect that lessen opioid addiction-related crises. My study promotes positive societal change by improving the safety of opioid administration and creating effective opioid addiction intervention programs for young adults. In Chapter 2, I discuss the literature search strategy, theoretical foundation, literature review related to the key variables, history of opioids, overview of nonmedical prescription opioid, prevalence of nonmedical prescription opioid use in Nigeria, determinants and social perspectives of nonmedical prescription opioid use, gaps in literature, summary, and conclusion.

Chapter 2: Literature Review

Literature Search Strategy

The study's literature search approach involved using keywords and databases to look for related topics covered in the literature review. The keywords include nonmedical prescription opioid use, opioid misuse, determinants of nonmedical prescription opioid use, integrated behavior model, consequences of nonmedical prescription opioid use in young adults, opioid deaths, opioid epidemics, opioid addiction, youths using nonmedical prescription opioids, nonmedical prescription opioid pain killer effects, opioid-related mental disorders, opioid laws and regulation, nonmedical prescription opioids deaths in Nigeria and worldwide. The databases and websites for the search included *International Journal of Drug Policy*, Social Science & Medicine, The National Library of Medicine (NLM), National Drug Law Enforcement Agency (NDLEA), NIDA, Nigerian Institute of Medical Research (NIMR), World Health Organization, National Agency for Food and Drug Administration and Control (NAFDAC), CDC Wonder, U.S. DHHS, Global Index Medicus, Medline/PubMed, Cochrane Library, Dissertations and Theses Global (ProQuest), Scopus, F1000 Research, and Web of Medicine. The inclusion criteria were that papers must have been published since 2017, in English, in peer-reviewed journals only, while the excluded papers were laboratory-based basic science and treatments. The literature search results include (a) initial results – 546 papers, (b) papers excluded – 512, and (c) papers included – 34.

Literature Review Related to Key Variables and/or Concepts

The study topics contained in the literature review are (a) history of opioids, (b) mechanism of opioid addiction, (c) overview of nonmedical prescription opioid use, (c) prevalence of nonmedical prescription opioid use in Nigeria, and (d) determinants and social context of nonmedical prescription opioid use.

History of Opioids

An opioid is a member of a class of medications that binds to opioid receptors in the central nervous system and is used to treat various degrees of pain (Hoffman et al., 2019). There are four kinds of opioids: (a) natural (morphine and codeine), (b) semi-synthetic (hydrocodone, oxycodone, heroin, and hydromorphone), (c) synthetic (fentanyl and tramadol), and (d) endogenous (methadone; CDC, 2021). Opioids were classified as narcotics under a single United Nations convention on narcotic drugs in 1961, which also established regulations for their access, use, and distribution by the International Narcotics Control Board, with the primary goal of reducing the sharp rise in opioid abuse and addiction (Hoffman et al., 2019).

From 2001 to 2003 and from 2011 to 2013, the rate of opioid analgesic use increased dramatically by a factor of two across the globe (Berterame et al., 2016). Tramadol usage was more common among teenagers and young adults in Nigeria, according to the 2017 UNODC report. Also, those with immunosuppressive illnesses like HIV and sexually transmitted diseases are more likely to use tramadol than healthy persons (UNODC, 2017).

Mechanism of Opioid Addiction

Continuous opioid use without considering the potentially harmful effects on one's health is called opioid addiction (Kolodny et al., 2019). The American Pain Society, the American Academy of Pain Medicine, and the American Society of Addiction Medicine reached a consensus on the definition of addiction in 2001. They agreed that addiction is a primary, chronic, neurobiological disease with genetic, psychological, and environmental factors influencing its development and manifestations characterized by behaviors like compulsive use, impaired control over behavior, and a host of other behaviors (American Academy of Pain Medicine, American Pain Society, & American Pain Society, 2001; Wu et al., 2006). In addition, prolonged opioid exposure, including prescription opioids for medical and nonmedical purposes, causes structural and functional changes around the brain responsible for motivation, reward, and impulse control (Kolodny et al., 2019; Upadhyay et al., 2010; Votaw et al., 2019).

With a sharp rise in the prescription of oxycodone and hydrocodone in the late 19th century, the United States is the top consumer of prescribed opioids globally (Kolodny et al., 2015). The skyrocketing opioid use in the United States are linked to the management of newborn abstinence syndrome, the rise in emergency room visits, and the overdose deaths attributed to the rising prescription opioid use (Patrick et al., 2012; Substance Abuse and Mental Health Services Administration, 2013).

Overview of Nonmedical Prescription Opioid Use

NMPOU can be described as taking an opioid in a way or dose that was not prescribed, taking someone else's prescription opioids, whether it is for a valid medical purpose, or taking an opioid for the thrill it gives off (NIDA, 2019). Tramadol, morphine, methadone, heroin, and fentanyl are the most popular opioids used for nonmedical purposes among young adults in Nigeria (UNODC, 2019).

Tramadol is an opioid drug that has become a rising public health concern in Africa among young adults due to its usage as an analgesic, for relaxation, to enhance sleep, and to increase energy, which can lead to abuse and addiction for both medical and recreational prescription opioid use (Salm-Reifferscheidt, 2018).

Heroin is a narcotic made from the opium poppy that can be consumed or smoked to relieve pain (John, 2021). It is the primary material used in legally synthesizing prescription medications, including morphine, codeine, and oxycontin, which can also be abused (John, 2021; Lord et al., 2009). The possible side effect of heroin use is lethargy and profound sleep (John, 2021). The long-term complications include infection of the heart's lining and valves, pulmonary conditions, persistent pneumonia, collapsed veins, seizures, blood clots, liver illness, arthritis, and other bacterial infections (John, 2021). The short-term complications of heroin usage include shallow breathing, foggy thinking, and uncontrollable itching sensations that lead to picking at the skin and compulsive scratching (John, 2021).

Additionally, there is a propensity for users to overdose, develop an addiction, and contract the diseases listed above, all of which may, directly or indirectly, result in death (John, 2021). Also, users who inject the substance might contract illnesses like HIV, AIDS, hepatitis B, and hepatitis C when they use non-sterile sharing needles (John, 2021). According to a 2015 report by the Center for Behavioral Health Statistics and

Quality in partnership with R.T.I International, most people use prescription opioids for nonmedical purposes because they experience pain in their bodies and internal organs, excitement after using them, depression, anxiety, emotions, and relaxation.

Prevalence of Nonmedical Prescription Opioid Use in Nigeria

Nigeria is a Sub-Saharan African nation in the western part of the continent of Africa. It consists of 36 administrative states and Abuja, which serves as Nigeria's federal capital territory (FCT) and is divided into the Northern and Southern regions of the country. Nigeria is politically divided into six geopolitical zones: North-Central, North-West, North-East, South-South, South-East, and South-West (UNODC, 2019). Approximately 177.5 million people live in Nigeria, bordered by the Bay of Benin and Gulf of Guinea in the south, the Republic of Benin in the west, the Republic of Cameroun in the east, the Republic of Chad, and the Republic of Niger in the north. Sao Tome and Principe, Ghana, and Equatorial Guinea, and those countries are its marine neighbors (Nations Online, 2021).

Ashrafioun et al. (2017) conducted a study that investigated the relationship between nonmedical prescription opioid use and suicidal ideation or attempts and discovered a significant association between younger people and higher rates of suicidal ideation or attempts. Prescription opioids are medications that licensed healthcare professionals (medical doctor, physician assistant, or nurse practitioner) prescribe to relieve moderate or severe pain. However, opioid abuse poses significant health risks (CDC, 2022). The CDC (2022) reported that from 2019 to 2020, there was a 38% increase in deaths involving opioids and a 17% increase in fatalities using prescription opioids. Additionally, in 2020, opioids were implicated in around 75% of the 92,000 overdose deaths.

According to Nigeria's 2017 national yearly prevalence of opioid usage by gender, there were roughly 3,010,000 (4.7%) men and 1,606,000 (3.3%) women (UNODC, 2019). The average age of first-time heroin users was 22 years old, and 87,000 (0.1%) of the young population in 2017 reported using heroin (UNODC, 2019). Women in this age range (18 to 25) were more likely than men to report injecting heroin (UNODC, 2019). According to the UNODC (2019), the estimated 2017 annual prevalence rate of nonmedical prescription opioid use in the states comprising the six geographical zones is as follows:

1. The North-Central geopolitical zone has seven administrative states: Plateau (11%), Nasarawa (11.8%), Niger (11.6%), Kwara (13%), Kogi (9.2%), FCT Abuja (10%), and Benue (8%).
2. The North-East has six administrative states: Adamawa (17%), Bauchi (16%), Borno (12%), Gombe (21.2%), Taraba (14%), and Yobe (18%).
3. The North-West geopolitical zone has seven administrative states: Jigawa (7%), Kaduna (10%), Kano (16%), Katsina (12%), Kebbi (12.6%), Sokoto (9%), and Zamfara (13.5%).
4. The South-East geopolitical zone has five administrative states: Abia (11.3%), Anambra (11.2%), Ebonyi (12.8%), Enugu (16.3%), and Imo (18.1%).
5. The South-West geopolitical zone has six administrative states: Ekiti (11.9%), Lagos (33%), Ogun (17%), Ondo (17%), Osun (14%), and Oyo (23%).

6. The South-South geopolitical zone has six administrative states, including Akwa Ibom (12.5%), Bayelsa (14%), Cross River (11.8%), Delta (18%), Edo (15%) and Rivers (15%).

Determinants and Social Context of Nonmedical Prescription Opioid Use

It is more beneficial to have a solid understanding of the predictive factors, social context, and particular perspectives of nonmedical prescription opioid use among young adults, which will assist researchers in developing opioid control, access, and distribution strategies to reduce or stop the prevalence rate and enhance positive social change in our society.

In a recent longitudinal cohort study, Cho et al. (2021) identified risk factors for nonmedical prescription opioid use in adolescents with or without a history of such use. Their findings revealed that cumulative behavioral health comorbidity indices were associated with sequentially higher odds of subsequent NMPOU for students with cannabis, drug, major depression, mania, and/or hypomania. However, the research gap is that their study focused more on the mental health problems of opioid users among students without considering the perceived intention, attitude, and behavioral control towards nonmedical prescription opioid use and lack the use of specific behavioral issues to prove their descriptive relationship among variables. With the help of IBM's attitude, perceived norms, and personal agency constructs, my study added to our knowledge of the effects of behavioral health issues and other susceptibility factors on the promotion of nonmedical prescription opioid use among adolescents and young adults. Therefore, there has not been any research into using the IBM to determine how attitude (experiential and instrumental), perceived norms (injunctive, subjective, and descriptive), and personal agency (perceived control and self-efficacy) affect young adults in Nigeria's nonmedical use of prescription opioids.

Barnett et al. (2019) conducted a study to determine the risk factors, such as other substance use, associated with nonmedical prescription opioid use among adolescents in the United States. The researchers discovered that nonmedical prescription opioid use was 1.5 times more likely among electronic vapor users and two times more likely among cigarette smokers. They examined the correlates of nonmedical prescription opioid use among the sampled teenagers using predictor variables such as demographics, mood, academic performance, and sleep. They found that participants under 15 were likelier to use nonmedical prescription opioids. However, this research only looked at societal and individual contexts as risk factors or determinants, ignoring attitudes, perceived intentions, and motivations for prescription opioid abuse. My study utilized the three IBM constructs to analyze the link between the independent factors and young adults' nonmedical prescription opioid use in Nigeria.

In a cross-sectional study on the connection between the prevalence of opioid abuse and opioid use disorder among young adults in the United States, Elliot and Jones (2019) revealed that young adult opioid users could not recognize withdrawal symptoms. Furthermore, they found that young adults are less likely to acknowledge withdrawal symptoms than older adults, who are more likely to have an opioid use disorder. My study filled the knowledge gap by using a behavioral model approach to alleviate the worries recognized by these age groups.

Jalali et al. (2020) used the social-ecological model to describe the conceptualization and the multifaceted complexity levels of the opioid epidemics using the multivariable risk factors of opioid misuse to capture the multidimensional issues based on the individual, interpersonal, communal, and societal levels. The researchers concluded that broader societal and environmental factors are the leading causes of the opioid epidemic. Jalali et al. created comprehensive measures to slow the sharp rise in nonmedical prescription opioid usage among young adults; however, their study could not explain the person's intention, attitude, emotions, sense of control, or self-efficacy. My study examined a person's intention, attitude, emotions, perceived control, and self-efficacy of the individual toward nonmedical prescription opioid usage using the three constructs of IBM.

In a longitudinal study to understand the national trends in the usage of prescription opioids for medical and nonmedical purposes by high school seniors between 1976 and 2015, McCabe et al. (2017) discovered that adolescents who reported medical and nonmedical prescription opioid use were likelier to indicate medical use of prescription opioids. The researchers also found that nonmedical prescription opioid use throughout a person's lifetime was less common and strongly associated with the medical use of prescription opioids throughout 40 years. Applying the behavioral constructs will help predict, monitor, and evaluate Nigeria's overall national trends of nonmedical prescription opioid use among young adults. This study is significant to my research because it provides an adequate understanding of the United States' overall national trends between medical and nonmedical use of prescription opioids among adolescents.

Peck et al. (2019) used an unweighted sample of 41 young adults (ages 18 to 25) from the 2016 National Survey on Drug Use and Health to investigate the relationship between educational level and substance misuse risk in young adults. They concluded that reasons for nonmedical use of prescription opioids did not differ as a function of academic status. Therefore, they suggested a need to address the nonmedical use of prescription opioids and improve pain management in these vulnerable populations. The most frequently cited reasons for past-year nonmedical use of prescription opioids were physical pain relief (47.6%), feeling good/getting high (19.8%), relaxing/relieving tension (13.2%), and experimenting/seeing what it feels like (6.8%). The researchers discussed the relative relationship between educational attainment and perceptions of nonmedical prescription opioid use in their study. It is pertinent to my own because it helped me to understand the motivation and perceived control for nonmedical prescription opioid use while controlling for education.

Rougemont-Bücking et al. (2018) investigated the relationships between traumatic stress, family functioning, peer influence, sexual assault, physical assault, neglect, and nonmedical prescription drug use in young men in Switzerland. They discovered that nonmedical prescription drug use, particularly opioid analgesics help, family functioning dependent on sleeping pills, and peer influence, appeared more consistently associated with the cumulative number of potentially traumatic events. At the same time, sexual and physical assaults committed by strangers showed a significant association with nonmedical prescription opioid use among young adults compared to assaults committed by a family member. This is significant to my research because it identifies socioenvironmental stressors (such as family functioning issues, peer group influence, traumatic stress, physical and sexual assault, and traumatic stress) that was used to address and lessen the public health crisis brought on by nonmedical prescription opioid use.

Theoretical Foundation

Fishbein's IBM served as this study's theoretical foundation. Theory- and model-based behavior treatments are more successful because they incorporate key elements required for behavior change. The broad definition of health behavior and its determinants is "those personal characteristics, including beliefs, expectations, motives, values, perceptions, and other cognitive elements; personality traits, including affective and emotional states and traits; and overt behavior patterns, actions, and habits that relate to health maintenance, health restoration, and health improvement" (Alemayehu et al., 2021). According to a review of online interventions for changing health behavior, theory-based interventions have proven more effective than those without theory at changing behavior. Advocates for theory-based therapies point out that in addition to being beneficial, this approach makes it possible to tailor behavioral interventions for use in a variety of settings (Alemayehu et al., 2021). It is crucial to measure the application of behavioral theories/models which propagate and inform theory/model based behavioral treatments. Therefore, the purpose of this study focused on evaluating the effectiveness of the IBM in predicting young adults' intention to engage in the targeted health behavior (nonmedical prescription opioid use) by assessing the model's constructs (experiential attitude, instrumental attitude, normative influence, perceived control, and self-efficacy).

There are three constructs in the IBM: (a) attitude, which has two subconstructs called instrumental and experiential attitudes; (b) perceived norm, which has three subconstructs called descriptive, subjective, and injunctive norms; and (c) personal agency, which has two subconstructs called self-efficacy and perceived behavior control (Fishbein et al., 2002).

Attitude

Attitude is a strong desire to engage in a particular behavior (The Behavior Institute, n.d.). A five-scale Likert measurement of respondents' intention to engage in nonmedical prescription opioid use was used to determine correlation coefficients and the degree of prediction based on the model construct questionnaires (Jebb et al., 2020). I measured the most common response when assessing attitudes using a 5-scale Likert measurement to comprehend the general sentiment of respondents. To determine where the respondents fit into the study category. For instance, if 85% of respondents answered strongly agree to attitude construct questions, I compared the percentages for each response using tabulation to display the breakdown of available response alternatives or answer options (See Table 5). Hence, my study investigated the correlation between respondents' attitude and their intention to engage in nonmedical prescription opioid use.

Experiential Attitude is a sensation that an individual gets toward executing an activity (Fishbein et al., 2002). Fishbein (2007) used this attitude sub-construct to describe a person's general mood, such as happiness or sadness, which is an affective state. For instance, those with a solid adverse emotional reaction to nonmedical prescription opioid use would be less likely to engage in the practice because of their unfavorable attitude (Fishbein, 2007).

In a longitudinal study, McCabe et al. (2019) investigated potential risk variables for adolescent substance misuse or disorders, including congestion, motivation, kind of opioid usage, frequency, quantity, peer group association, and initiation history of prescription opioid use. Researchers discovered that most teenagers who used prescription opioids for purposes other than pain treatment reported using them occasionally or frequently, indicating that opioid analgesics had significant potential for abuse. However, they didn't consider the intention or any other health behaviors which young adults might experience leading to opioid misuse in their study. The three constructs of IBM were used to analyze the predictive relationships between the dependent variable leading to morbidity and death rates among young adults between 18 and 25.

Instrumental attitude is the second sub-construct of attitude in Fishbein's Integrated Behavior Model, and it refers to a person's expectations for the behavior's results (Fishbein et al., 2002). According to Fishbein's Integrated Behavior Model, a person will have a more positive attitude about engaging in an activity if they firmly believe the benefits exceed the adverse outcomes.

Bakhshale et al. (2019) examined the association between negative affectivity and nonmedical use of prescription opioids in two sub-samples of people with and without pain and among racially and ethnically diverse young adults attending a sizable Southwestern State University. According to their research, targeting emotion dysregulation may be one therapeutic strategy to reduce prescription opioid nonmedical use in the context of negative affectivity among college students. However, Bakhshale et al. (2019) did not assess individual attitudes [instrumental and experiential] and perceived intention behind nonmedical prescription opioid use among college students. They only examined the challenges of emotion dysregulation and the association between negative affectivities. My research focused on identifying any significant correlation between respondents' attitude and intention to engage in nonmedical prescription opioid use among young individuals in Nigeria.

Perceived Norm

The perceived norm has two subconstructs, descriptive and injunctive norms. This construct will evaluate young adult's beliefs and expectations about nonmedical prescription opioid use and how it really affects them towards performing a healthy behavior. My study examined the correlation between the normative influence and respondents' intention to engage in nonmedical prescription opioid use.

Rice and Klein (2019) conducted a study to examine how attitudes and perceived norms interact with health-related behaviors among the United States adolescent populations. They discovered that social norms as individuals perceive them may considerably impact both health-improving and health-promoting behaviors, especially when they are consistent with parental standards or attitudes regarding those behaviors.

Descriptive norm is the perception of what other people typically do, whereas an injunctive norm is the perception of what others believe should be done (Fishbein, 2000; Fishbein et al., 2002). By distinguishing between descriptive norms (i.e., how other people often behave) and injunctive norms (i.e., what other people approve of) and more accurately assessing more specific forms of behavior, later studies have clarified processes by which both peer and parental norms may influence adolescent behavior (Williams & Sanchez, 2013). For instance, a survey of teenagers in the UK found strong correlations between descriptive norms and teens' dietary practices (consumption of fruits and vegetables, beverages with added sugar, and unhealthy snacks) but no correlation between injunctive norms and adolescents' nutritional practices (Lally et al., 2011).

Injunctive norm is a subconstruct of the perceived norm which demands that a person be aware of what other people want them to do but is far more potent when there is an implicit social threat. Breaking injunctive standards is expected to result in social consequences, such as reprimands or exclusion (Rice & Klein, 2019; Sheeran, 2002). Being excluded, even for a short time, can be psychologically uncomfortable. Therefore, people are inclined to avoid it.

Reid et al. (2013) conducted a study that examines the predictive relationship between attitudes and injunctive norms with improving sun protection and tanning in white women. They found that attitudes mediate the influence of injunctive norms on behavior. Still, descriptive norms directly relate to behaviors, providing additional evidence of the interrelationships between norms and attitudes. In another study, Reid et al. (2018) investigated the association of perceived norms with intentions to learn genomic sequencing results and found descriptive and injunctive norms play major roles in genomic sequencing decisions. This is significant to my research because their research helped me to understand the value of rectifying erroneous perceptions of injunctive norms in fostering healthy behaviors. It is more beneficial, especially when investigating university students' injunctive norms perception for nonmedical prescription opioid use.

Personal Agency

The level of control that young adults perceive they have over their use of nonmedical prescription opioids was evaluated using this construct. It has two subconstructs (self-efficacy & perceived behavioral control).

Self-efficacy is a subconstruct of personal agency and can be defined as the capacity to confidently carry out an activity (Fishbein et al., 2002). Self-efficacy refers to a person's level of assurance in their ability to carry out the behavior in the face of various obstacles or problems (Glanz et al. 2015). Papazisis et al. (2018) conducted a cross-sectional study with medical students to examine the prevalence and motivation of nonmedical use of prescription pharmaceuticals and their link to the use of illegal drugs, alcohol, and cigarettes. The researchers discovered a connection between the overuse of tranquilizers and illicit drugs, a link between opioid, sleeping, and stimulant usage, and the misuse of tobacco and alcohol. This is significant to my study because the authors' research, which included motivation as one of the determinants of nonmedical prescription opioid use among medical students, revealed evidence of self-efficacy in the wake of the students' confidence in abusing illegal drugs substances or opioids to boost motivation. The association between nonmedical prescription opioid use and personal agency were investigated at the individual level among young adults.

Perceived behavioral control is another subconstruct of personal agency and can be defined as the perceived difficulty or simplicity of carrying out the behavior (Fishbein et al., 2002). Perceived control refers to a person's sense of control over behavioral performance. It will be based on how much a person's perceptions of the degree of various environmental factors make it easier or more complex to perform the behavior (Glanz et al., 2015). Wright and Ramirez (2021) found that adolescents with long-term health issues have poorer mental health and may turn to nonmedical use of prescription opioids for pain relief when not given standard care. The study examined the relationship between the nonmedical use of prescription opioids and suicidal behaviors among adolescents. Their study elaborated on how long-term health problems have been a significant challenge for these age groups because they do not perceive control over their behavior, leading to an increased rate of nonmedical prescription opioid use. Their study benefitted my study by using behavior constructs to examine the individual correlates with nonmedical prescription opioid use and provide a behavioral approach to long-term health problems facing young adults' opioid misuse and addiction.

Gaps in the Literature

Elliot and Jones (2019) observed that young adults are less likely to acknowledge opioid withdrawal syndrome when they conducted a cross-sectional study examining the association between the rate of opioid usage and opioid use disorder among young adults in the United States. However, the factors at the individual-level, such as attitude, intention, and behavior control, were not examined in their analysis. Thus, more research is required to fully understand how to reduce the anxiety of these young adults and enhance their behavioral aspects.

Jalali et al. (2020) applied the socioecological framework to investigate the interactions between social networks, the environment, and human characteristics, including knowledge and conduct. Jalali and colleagues concluded that both internal and external perceptions affect opiate abuse. Moreover, they did not assess people's views, intentions, or self-efficacy about opiate misuse in their study. By analyzing the association between the three constructs of the Integrated Behavior Model and nonmedical opioid use, my study filled this knowledge gap.

Barnett et al. (2019) investigated the predictive relationship between risk factors (academic performance, sleep, mood, and demographic characteristics) and nonmedical prescription opioid use in a cross-sectional study. The researchers discovered that adolescents aged 15 are likelier to begin nonmedical prescription opioid use. However, their study did not delve into the motivations and behaviors that drive the continued use of nonmedical prescription opioids. This study bridged the gap by investigating the perceived norm, attitude, and personal agency. It provides an effective public health intervention program to improve positive social change in our society through behavior modification.

Summary and Conclusion

In Chapter 2, I reviewed current research literature, outlined the process of conducting a literature search using topic-related keywords, identified literature gaps, and determined the overall scope of the research problem. The literature review for this study examined recent research for determinants of nonmedical prescription opioid use among adolescents and young people aged 15 to 25 years based on individual, social, environmental, and physical factors. IBM is the proposed theoretical framework for the study, and I provided a justifiable reason for its use in this study. Several researchers have used various theoretical models to investigate and assess the factors that promote opioid misuse and addiction, but no researcher(s) have used IBM to evaluate an individual’s intention, self-control, and sociobehavioral perspectives that influence opioid misuse among young adults aged 18 to 25 years.

A longitudinal study investigating the national trends of nonmedical prescription use among teenagers and young adults between 1975 and 2015 revealed that youths aged 18 to 25 are more likely to continue nonmedical prescription opioid use over a 40-year period (McCabe et al., 2017). In Nigeria, the rate of drug use, including medical and nonmedical prescription opioids, is significantly higher than the global annual prevalence of any drug use among adults, of 5.6% in 2016 (UNODC, 2018). The rise in opioid misuse among university student populations has been a public health concern (Keyes et al., 2014). Studies have shown that university/college students are more likely to share and store medications, including opioids, in unsafe conditions, increasing the likelihood of prescription misuse (Keyes et al., 2014). Tramadol, morphine, methadone, heroin, and fentanyl are the most used nonmedical opioids among young adults in Nigeria (UNODC, 2019).

In conclusion, opioid abuse is a global crisis that seriously affects people’s physical health, energy, mental state, increases stressful condition, and enormous financial burdens on families, friends, and society (U.S. DHHS, 2016). The findings promote positive social change by establishing effective policies and laws that monitor medical and nonmedical prescription opioids in higher institutions, prevent young adults aged 18 to 25 from obtaining nonmedical prescription opioids from street vendors, and eliminate opioid addiction through improving medication administration safety. In addition, this study provides a long-term roadmap for future researchers as well as potential solutions such as limiting prescriptions, informing people about better pain management techniques, and educating university students and other uneducated young adults aged 18 to 25 years about the risks of taking nonmedical prescription opioids and discouraging recreational use.

In Chapter 3, I describe my study's methodology, including the study design, sampling techniques, data collection instrumentation, measurements, and other statistical approaches.

Chapter 3: Research Method

The purpose of this study focused on examining the predictive relationship between three constructs of IBM and NMPOU among young adults, while controlling for age, gender, and educational level. This chapter includes the research design and rationale, methods, threats to validity, and ethical procedures.

Research Design and Rationale

This study employed quantitative correlational study using a survey approach to data collection. The independent variables in this study are three constructs of the integrated behavior model (i.e., attitudes [instrumental and experiential], perceived norms, and personal agency [perceived control and self-efficacy]), which were measured using the IBM questionnaires in a 5-point Likert scale. In contrast, the controlling variables are demographic factors (age, gender, and educational level), and the dependent variable is nonmedical prescription opioid use. I examined predictive relationships between the independent and dependent variables in this study.

Quantitative studies are useful when examining the correlations between certain variables (Creswell, 2014). Quantitative research strategy is a method of data collection and analysis that emphasizes numbers and figures (Daniel, 2016). A quantitative design was suitable for this study because it examined the associations between certain variables. Despite the usefulness of qualitative analysis for collecting extensive data about a topic, the data needed to conduct inferential analyses, such as the regressions, necessitated a quantitative approach to answer the research questions in this study (Merriam & Tisdell, 2016; Williams, 2017). Given that a mixed-methods study uses both quantitative and qualitative data, I believed that a mixed-methods approach would not have been appropriate for this study if qualitative data had not been relevant for addressing the research objectives set forth for it.

According to Simpson (2015), surveys are appropriate for gathering quantitative data, particularly when a researcher has a large sample size. A survey approach was suitable for data collection in this study since I gathered quantitative data from a sizable sample of university students (both males and females). A survey approach was also suitable since it enables me to produce the quantitative data required for inferential analyses, such as the regressions required to address the research issues in this study (Harris, 2021; Simpson, 2015).

Correlational designs are used in research when the study aims to determine the degree of association between two or more variables (Wang & Cheng, 2020). Cross-sectional studies, for example, can only be correlated if an association between variables is observed (Solem, 2015; Wang & Cheng, 2020). I selected a correlational research design because it allows me to examine the degree of association between two or more variables and does not require random assignment of subjects (Creswell, 2009, 2013).

According to Frankfort-Nachmias et al. (2015), correlational research designs assist researchers in evaluating relationships between variables and describing patterns of relationships without concluding causation in those relationships. This design does not require manipulation or intervening variables (Frankfort-Nachmias et al., 2015). In addition, a correlational research design allows data collection and recording in a natural setting, allowing the researcher to disapprove or approve the study's hypotheses and explain the relationship pattern observed between variables (John, 2021; Koppoe, 2018).

The correlational design allows researchers to study one group or section at a time in a natural setting and is appropriate for social science research that involves data collection via surveys and questionnaires (Frankfort-Nachmias & Nachmias, 2008; Sheperis et al., 2010). However, correlation design has its disadvantages: (a) it cannot demonstrate causations for observed patterns even if the process recognizes data sequences, background, and behaviors (Koppoe, 2018); and (b) in contrast to longitudinal research designs, which allow manipulations and the observation of changes in the dependent variable over time, research participants can only relate information about attitudes, beliefs, behaviors, and opinions that are very recent and current situations, which do not support in-depth analysis (John, 2021; Sheperis et al., 2010).

Methodology

The methodology is divided into five main categories. In this section, I first discuss the population of the study, followed by the strategy for sampling, the procedures for taking samples, the sampling frame, and sample size estimation. Next, I describe how I identified potential participants for this study, the inclusion criteria for participation, and the methods I employed for collecting data. After that, I describe in detail the data collection instruments and how the study's variables were operationalized. Finally, I describe how I evaluated the data after collection.

Population

The target population for this study were university students (aged 18–25) enrolled in a Nigerian nationally accredited university. I decided to conduct the online survey research in a higher education institution because the university has a large population and various academic disciplines with diverse cultures and ethnic backgrounds. In the 2018/2019 academic year, Nigerian universities had 1.8 million undergraduate students (1,010,609 male and 788,349 female) and 242,000 postgraduate students (150,319 male and 92,014 female; Sasu, 2022). As a result, my decision to use this university for data collection provided data that can be generalized to other male and female young adults aged 18–25 without secondary or tertiary education in Nigeria.

Sampling and Sampling Procedures

Sampling Strategy

I employed purposeful convenience sampling to recruit university students (18–25 years old) who met the inclusion criteria. A purposeful convenience sampling allows for the quick collection of data from eligible participants based on their convenience, accessibility, and personal experience (Frankfort-Nachmias et al., 2015; John, 2021). The disadvantage of the convenience sampling strategy is that specific sampling unit generalizability to other populations can be problematic (Frankfort-Nachmias et al., 2015, John, 2021). A purposeful convenience sampling is cost- and time-effective (see Frankfort-Nachmias et al., 2015). Although the sampling approach is subjective, this can be a drawback because it can be challenging to estimate the likelihood of including a specific sampling unit that looks to be representative of the population (Frankfort-

Nachmias et al., 2015). I contemplated combining snowball sampling with purposeful convenience sampling to discover extra study participants who might not have seen the recruitment materials, but I decided against it since I wanted to maintain complete anonymity while collecting the data via online survey. Snowball sampling is a recruitment strategy in which research participants are invited to help researchers find other potential subjects (Kirchherr et al., 2018). The advantages of snowball sampling include its time- and money-saving features (Trochim, 2006). The snowball sample strategy can only be generalized to similar groups or people in comparable cities, which is a limitation (John, 2021).

Random sampling was an alternative sampling strategy I considered but decided not to use for this study. Random sampling is a probability sampling strategy used in research when two or more subgroups in a population are likely to differ significantly in their responses; and it is used if the people will be split into groups or a proportion of the sample has similar characteristics (Frankfort- Nachmias et al., 2015; John, 2021). The advantage of this sampling method is that it allows for the random selection of equal-sized group samples with the necessary independent variable characteristics, and findings can be generalized to other populations (Frankfort-Nachmias et al., 2015). However, the procedure can be time-consuming and costly (Frankfort-Nachmias et al., 2015; John, 2021).

Inclusion and Exclusion Criteria

I recruited university students who voluntarily wanted to participate in the online-based survey and who were between the age of 18 and 25; able to read, speak and understand English language; and had a history of opioid use. Potential participants were excluded from participation if they did not meet the inclusion criteria.

Sample Size Calculation

The sample size is essential in determining the validity and reliability of the study's findings and their potential generalizability (Frankfort-Nachmias et al., 2015). Because it is always possible that not enough participants may volunteer to take part in the study, sample size considerations are especially important when samples depend on participant self-selection (Frankfort-Nachmias et al., 2015). I used G*Power software (Version 3.1.9.7) to conduct a priori analysis to establish the required sample size for this investigation. G*Power is software used to (a) calculate statistical power and the required sample size; (b) compute statistical power analyses for various *t* tests, *F* tests, *y2* tests, *z* tests, and exact tests; and (c) compute effect sizes and display the results of power analyses graphically (Faul et al., 2009). G*Power helps to determine the number of model measurement survey respondents. I utilized a power of .95, an error of probability of.05, and a medium effect size of .15, which displayed an appropriate sample size and eliminated the problem of too small or too large a sample size (Faul et al., 2009). Based on this research, the model measurement survey has a total sample size of 154 samples obtained using p = .5 with a 95% confidence interval and a 5% margin of error which would be required to reach a conclusion of significance. The sample size calculation using G*Power was as follows:

***F* tests:** Linear multiple regression: Fixed model, R^2 increase

Analysis: A priori: Compute required sample size

Input:	Effect size f^2	=	0.15
	α err prob	=	0.05
	Power (1-β err prob)	=	0.95
	Number of tested predictors	=	6
	Total number of predictors	=	6
Output:	Noncentrality parameter λ	=	21.9000000
	Critical *F*	=	2.1644088
	Numerator *df*	=	6
	Denominator *df*	=	139
	Total sample size	=	146
	Actual power	=	0.9507965

Procedures for Recruitment, Participation, and Data Collection

Recruitment

Three weeks before the data collection via online survey, I posted flyers on the university's social media platforms, such as Facebook, and the student affairs' campus bulletin board. The flyers contained information about the study, inclusion criteria, and the time frame for the online survey. I stated on the flyers that potential participants could fill out the data collection instruments electronically by using the online survey link provided on the flyers. I also stated on the flyers that all responses remain anonymous. Participants who indicated interest were asked to agree to the terms of participation in the study by clicking the accept button, at which point they were directed to the first survey item. Participants who did not agree to the terms of participation in the study were directed to another webpage where they were thanked for their time and then exited from the survey. The online version was less expensive and takes less time. Therefore, the online version of the data collection instruments was declared open on the date specified on the flyers. The online-based survey was closed on the date specified on the flyers and upon collection of the minimum sample size calculated using G*power.

The online-based version has the advantage of promoting more involvement from students who do not wish to be physically recognized as opioid addicts and afraid of legal consequences but use chronic opioids for nonmedical purposes. Hence, the use of online-based survey version promoted anonymity and confidentiality of the participants' identities. This online-based version was done using Qualtrics. Qualtrics is a reputable and market-leading supplier of web-based survey solutions used to store and protect the electronic data that will be gathered there (Qualtrics, 2021). Internet Protocol (IP) addresses are password-encrypted, blocked, and not tracked by Qualtrics, and the privacy of users is not at risk (Qualtrics, 2021).

Data Collection

The data collection process was conducted in a single form: online-based survey. Participants completed the online survey using the link in the flyer. The inclusion criteria were included in the initial screen, and each potential participant was asked if they meet the requirements. Participants were given instructions on how to print or save a copy of the implied consent form for their records. After reading the implied consent, individuals were asked if they would agree to take part in the study at the end of the form. Potential participants who answered "no" were exited from the survey and thanked for their time.

Those who responded “yes” to the implied consent were asked to voluntarily complete the online survey and were directed to the demographic form (see Appendix A) and the IBM questionnaires for the primary outcome and latent constructs (see Appendix B).

Instrumentation

The initial phase on the online survey was the implied consent form, which the participants had to read and understand before completing the online survey and which served as a consent to the study. The implied consent form elaborated the purpose of the study, risks, and benefits of participating in the study, masking of the organization in partnership and how participants’ information will be anonymous.

I created and used the demographic form to collect demographic information from participants, such as age, gender, and educational level.

The IBM Questionnaires for Primary Outcome/Latent Constructs is a self-report survey to assess the descriptive relationship between the latent constructs and the primary outcome using the 5-point Likert scale. The Likert scale is a rating scale used to determine opinions, attitudes, and behaviors (Jebb et al., 2020). For example, researchers used the Likert scale embedded in the nonmedical use of prescription opioids questionnaire for university students to assess the frequency of opioid misuse (Mateu-Gelabert et al., 2015). The IBM self-reported questionnaires employed the 5-point Likert scale measurement in rating participants’ responses to the behavioral surveys probing the intensity and frequency, opioid sources, age at first-time opioid use for the primary outcome, commonly available opioids in Nigeria, and other construct surveys.

Participants selected the option that best reflected their feelings about the question from the 5-point Likert scale (*strongly agree* = 5 to *strongly disagree* = 1).

The Likert scale with a 5-point bipolar type helped establish and understand respondents' attitudes and feelings about behavior in a series of one answer response out of the 5-point questionnaires of different weights. For instance, participants who have a significant negative emotional reaction to consuming nonmedical prescription opioids are less likely to engage in the practice by having a negative attitude about nonmedical prescription opioid use. The Likert scale captured the level of feelings or agreement regarding the topic in a more distinct approach because participants were presented with a range of possible answers that will measure attitudes (Jebb et al., 2020).

Previous studies have utilized identical IBM constructs precursor questions that were used in creating IBM questionnaires for this study to examine the relationship among the independent, dependent and covariates. Their study outcomes validated the instrument for future research and remain available on internet public domain without personal ownership that can require seeking for an approval to use, reconstruct or amend the precursor questions.

For example, Alemayehu et al. (2021) employed 5-point Likert measurement in determining the degree to which the IBM's constructs explain people's desire to engage in early detection and treatment of sexually transmitted illnesses as a beneficial behavior for HIV prevention. Their research validated the use of IBM questionnaires embedded with a 5-scale bipolar Likert scale which I employed for my research.

Martinez (2017) conducted a study using IBM to assess how attitude towards e-cigarettes, perceived norms concerning e-cigarette use, and the perceived ability to use e-cigarettes drive young adult's intention and e-cigarette use behavior. Martinez employed similar precursor questions to those adopted in my study to investigate the association between the three constructs of IBM and young adult's intention and e-cigarette use behavior. The two precursor questions used for the primary outcome in the IBM questionnaires have been used in the 2013–2014 Population Assessment of Tobacco and Health (PATH) study wave 1 baseline adult questionnaires conducted by the U.S. DHHS, whose primary objective was to examine and monitor between-person differences and within-person changes in behaviors, attitudes, risk perceptions, biomarkers, and health outcomes related to tobacco use. Hence, I developed this survey with Likert scale upon validation from previous studies demonstrating relationship between the IBM latent constructs, covariates, and primary outcome.

Branscum and Lora (2017) conducted a study that operationalized the IBM to identify significant theory-based determinants of maternal monitoring of fruits and vegetables, among low-income, Hispanic mothers of 2–5-year-old children. The researchers adopted a similar IBM survey with a unipolar 5-point semantic differential scales ranging from *strongly disagree* (1) to *strongly agree* (5), which I applied for my study survey with the 5-scale bipolar type of Likert scale. Their study adopted this instrument to measure the behavioral intentions pertaining to the mothers' willingness to monitor the child's fruit and vegetable consumption. Their findings suggested that all scales on the instrument were valid and reliable, except the autonomy scale for self-efficacy, a subconstruct of personal agency which question did not follow the 5-point semantic differential scale (Branscum & Lora, 2017).

Operationalization of Variables

Tables 1 lists the covariates and dependent and independent variables employed in this study, along with their subcategories and values.

Table 1

Operationalization of Variables

Data collection instrument	Variable name	Values within variable	Variable level
		Demographic variables	
Demographic form	Age	Nominal scale Categorical	Actual age in years
	Gender	Nominal scale Categorical	Male, female
	Educational level	Ordinal scale Continuous	Freshman (100 level) - 0 Sophomore (200 level) - 1 Junior (300 level) - 2 Senior (400 level) - 3 Master's degree (500 level) - 4 PhD degree (600 level) - 5
		Independent variables	
IBM constructs	Attitude	Ordinal Categorical	Strongly agree (5) to strongly disagree (1)
	Perceived norm	Ordinal Categorical	Strongly agree (5) to strongly disagree (1)
	Personal agency	Ordinal Categorical	Strongly agree (5) to strongly disagree (1)
		Dependent variable	
IBM Questionnaire	Frequency of opioid misuse	Ordinal	Never Seldom Sometimes Often Very often

The IBM questionnaires and demographic characteristics survey were quantitatively and subjectively used to collect information on attitudes, perceived norms, personal agency, age, gender, educational level, and nonmedical prescription opioid use. The dependent variable is nonmedical prescription opioid use, and the independent variables are the three constructs of the integrated behavior model: attitude (experiential and instrumental), perceived norms (injunctive and descriptive), and personal agency (perceived control and self-efficacy). The controlling variables are age, gender, and education.

A representation of the analysis's variable breakdown concerning the definition and kind of measurement are displayed in Table. Table 1 lists the variables, their definitions, measurement ranges, and values within each variable. The two categorical variables (age and gender) and one continuous variable (educational level) are utilized as control variables in the demographic form. Age measured using a nominal scale, whose values correspond to years of real age. Gender measured using a nominal scale, whose two possible values correspond to male and female. The values for educational level are categorized as freshman, sophomore, junior, and senior on an ordinal scale. All three of the IBM latent constructs are ordinal categorical variables with values from 5 (*strongly agree*) to 1 (*strongly disagree*) using the Likert scale. The IBM questionnaire indicators for the dependent variable (frequency of opioid use) were categorically measured using an ordinal scale, with values ranging from everyday, someday, once a month, not at all, and quit.

Data Analysis Plan

I employed the statistical package for social sciences (SPSS) software version 28 to analyze the data. The creation of descriptive data was the first stage used to analyze the data and test hypotheses (Williams et al., 2013). Upon the completion of the data collection period, I commenced the data analysis process. The first step in this process started by organizing the data I collected online. I organized the data by exporting the online survey responses from Qualtrics by the participants into an Excel spread sheet. Upon completion of correctly inputting the data from the online surveys to Excel spread sheets, I uploaded the data to SPSS for analysis directly from Qualtrics. I reexamined the data to guarantee that the surveys obtained from the online surveys were accurate to identify any human errors, inconsistent codes, or outliers. Outliers can be defined as the extreme numbers at one or both extremes of a sample distribution resulting from incorrect data input or individuals who do not belong to the target population (Jones, 2019). I created scatter plots (H) to determine whether the linearity assumption was met and to seek outliers. Cases that have data for at least 75% of the variables were retained in the data. I shall regard the missing answers as missing values and omitted those particular "missing values" from the analysis of that same variable (John, 2021; Mertler & Vannatta, 2013). However, there were no missing values observed in the analysis.

Research Questions and Hypotheses

RQ1: Is there an association between attitudes (instrumental and experiential]), as measured by the 5-point Likert scale, and nonmedical prescription opioid use, as measured by the IBM questionnaires, controlling for age, gender, and educational level.

$H_0$1: There is no relationship between attitudes [instrumental and experiential] (measured by the 5-point Likert scale) and nonmedical prescription opioid use (measured by the IBM questionnaires), controlling for age, gender, and educational level.

H_a1: There is a relationship between attitudes [instrumental and experiential] (measured by the 5-point Likert scale) and nonmedical prescription opioid use (measured by the IBM questionnaires), controlling for age, gender, and educational level.

RQ2: Is there an association between perceived norms [descriptive, subjective, and injunctive] (measured by the 5-point Likert scale) and nonmedical prescription opioid use (measured by the IBM questionnaires), controlling for age, gender, and educational level.

H_02: There is no relationship between perceived norms [descriptive, subjective, and injunctive] (measured by the 5-point Likert scale), and nonmedical prescription opioid use (measured by the IBM questionnaires), controlling for age, gender, and educational level.

H_a2: There is a relationship between perceived norms [descriptive, subjective, and injunctive] (measured by the 5-point Likert scale) and nonmedical prescription opioid use (measured by the IBM questionnaires), controlling for age, gender, and educational level.

RQ3: Is there an association between personal agency [perceived control and self-efficacy] (measured by the 5-point Likert scale) and nonmedical prescription opioid use (measured by the IBM questionnaires), controlling for age, gender, and educational level.

H_03: There is no relationship between personal agency [perceived control and self-efficacy] (measured by the 5-point Likert scale) and nonmedical prescription opioid use (measured by the IBM questionnaires), controlling for age, gender, and educational level.

H_a3: There is a relationship between personal agency [perceived control and self-efficacy] (measured by the 5-point Likert scale) and nonmedical prescription opioid use (measured the IBM questionnaires), controlling for age, gender, and educational level.

Analysis Techniques

The analysis technique was grouped into two phases (descriptive statistics and multiple linear regression) to examine the predictive relationship between variables and the hypotheses of the three research questions.

Descriptive Statistics

I conducted descriptive statistics to characterize the demographic information that offers broad details about the sample. The descriptive statistics include mean, frequency, distribution and percentages, standard deviation, and measure of a relationship. Here, the descriptive statistics assessed categorical dichotomous and ordinal items by examining the proportion of young adults on nonmedical prescription opioid use that answered 'strongly agrees' to each response column (Martinez, 2017).

Multiple Linear Regression

Multiple linear regression is the statistical data analysis that is appropriate for this study. To measure, investigate, and comprehend correlations between two or more variables, multiple linear regression analysis was originally used for this purpose. In this study, the multiple linear regression model was employed to predict the value of dependent variable Y (nonmedical prescription opioid use) starting from the knowledge of several independent variables (attitude, perceived norms, personal agency, age, gender, and educational level). The applicability of the technique for the examination of the quantitative variables pertinent to the main research topic in this study made multiple regression analysis useful. A data analysis technique called multiple linear regression is used to investigate the connections between predictor variables and an outcome variable (Montgomery et al., 2015). Two steps must be completed in the multiple linear regression data analysis phase: (a) correcting any assumptions that are violated when using multiple linear regression analysis, and (b) using multiple linear regression procedures (Williams et al., 2013). In the last phase, I utilized the findings from the earlier studies to determine whether to reject the null hypothesis.

According to Zikmund et al. (2010), hypothesis testing is a process based on sample data and probability theory. In contrast to the alternative hypotheses, which assert that there are statistically significant relationships among or across variables, the null hypotheses assert that no such relationships exist (Martinez-Camblor & Corral, 2012). The degree of significance must be taken into consideration when deciding whether to reject or accept a null hypothesis in null hypothesis significance testing (Lakens, 2013).

There were several crucial phases required in testing a hypothesis. The null and alternative hypotheses were first stated, then the proper test statistic and level of significance were chosen (Lakens, 2013). When sample sizes are bigger than 30, the t-distribution is seen as being equivalent to the normal distribution. In other words, the t-distribution approaches a normal distribution as sample size increases (Ciolino et al., 2015). In peer-reviewed research, the study of certain statistical tests used to analyze correlations, connections, and interactions is growing (Akhtar et al., 2016). Multiple regression is the ideal statistical method for data analysis in the investigation of potential correlations between many variables (Cohen et al., 2013). Multiple linear regression is a statistical method that makes use of several explanatory variables to predict the outcome of a response variable (Trunfio et al., 2022). Multiple linear regression represents an expansion of the single-explanatory variable known as the simple linear regression model (Trunfio et al., 2022).

Given that there were multiple predictor variables in this investigation, a simple/bivariate linear regression analysis was not appropriate. According to Harrell (2015), a researcher uses linear regression analysis to look at the linear relationship between the predictor and criterion variables. Given that bivariate models concentrate on a single predictor variable, simple linear regression was not viable for this study's analysis (Cohen et al., 2013).

Zikmund et al. (2010) claimed that analyzing the results of multiple linear regression is a straightforward procedure that involves the F-test, which is beneficial to determine whether the model is sufficient to meaningfully predict the dependent variable.

To comprehend each regression result, one must first understand the model's overall significance level (Zikmund et al., 2010). Based on the methods and decisions that Lakens (2013) outlined as standard in academic research, the alpha, or level of significance, for this study was set at.05. I rejected the null hypothesis if there is a statistically significant link between the related predictor variable and the dependent variable if the p-value is less than the significance level (α =.05). For the second step, I examined the R2 coefficient of determination to ascertain the percentage of variance accounted by the regression model (Nega, 2017; Zikmund et al., 2010). The degree of statistical correspondence between the data and the fitted regression line is quantitatively represented by the R2 value (Zikmund et al., 2010).

The following six hypotheses was proven prior to creating the multiple linear regression model in this study:

1. The scatter plot is used to check the linear relationship between the independent and dependent variables (Trunfio et al., 2022).
2. Lack of multicollinearity. Multicollinearity is used to evaluate the essential changes in the values of the regression coefficients. Tolerance = 1-R2i and Variance Inflation Factor (VIF) = 11−R2i—where R2i is the portion of the variation in the dependent variable that is foreseeable from the independent variables and is used to validate this assumption (Trunfio et al., 2022).
3. When the residuals are independent, the result of the Durbin-Watson statistical test should be analyzed (Trunfio et al., 2022).
4. The residual variance is constant. Therefore, developing a graph of "standardized residuals" versus "standardized expected value" was used to confirm it (Trunfio et al., 2022).
5. The residuals are evenly distributed. This assumption was confirmed using a quantile-quantile (Q-Q) plot (Trunfio et al., 2022).
6. When there is the presence of outliers. The Cook's distance values consistently less than one guarantees the absence of outliers (Trunfio et al., 2022).

Multicollinearity occurs when one or more independent variables employed in a regression analysis interact with one another in a way that magnifies their association to the dependent variable, causing the analysis results to be skewed (John, 2021).

According to Mertler et al. (2021), multicollinearity is avoided by removing or replacing one or more highly correlated variables when there are two or more variables. I performed a multiple correlation analysis and VIF to see if any variables were significantly associated (Mertler et al., 2021). When searching for total independence between variables for the best linear combination, better results prediction occurs at intercorrelation levels of 0.8 and higher (Mertler et al., 2021).

VIF was used to assess the presence of multicollinear connections for specific predictor IVs (Mertler & Vannatta, 2013). Mertler et al. (2021) stated that VIF could be computed using the formula: VIF (1-Rj2). When the VIF values for each predictor is greater than 10, it shows multicollinearity and is a massive concern to the researcher(s) in a study (Mertler et al., 2021). Hence, when the data from one variable was recorded by another and no data was lost, the problematic variable would be eliminated from the study (John, 2021).

Data entry Technique and Model Selection

There are three appropriate methods for multiple linear regression; forward selection, backward elimination, and stepwise regression (Mertler et al., 2021). The stepwise regression method combines forward selection and backward elimination (Mertler et al., 2021). The stepwise regression method allows researcher to add and remove independent variable (IV) as needed for each step that were not significant at a high percentage to the dependent variable (DV) and estimate how much each IV would contribute if it were to enter the equation (John, 2021; Mertler et al., 2021). In addition, the benefit of utilizing stepwise which combine the backward elimination and forward selection methods helps to guarantee that the equation contains only significant predictors (John, 2021; Mertler et al., 2021). For this study, I performed enter multiple regression modeling to run multiple linear regression in SPSS. Finally, the following equation was used to calculate the multiple linear regression for DV:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \ldots + \beta_{12} x_{12} + \varepsilon$$

Where y is the nonmedical prescription opioid use, β_0 is the intercept value, x_i are the six independent variables (attitudes, perceived norms, personal agency, age, gender, and educational level), β_i are the estimated regression coefficients of respective independent variables, and ε is the model error (means the variation of our estimate of y with respect to the real value). A partial F test for significance was conducted for every predictor variable to determine the level of contribution to the overall prediction (Mertler et al., 2021).

Threats to Validity

Validity is the veracity and accuracy of inferences made after a hypothesis has been tested. According to Frankfurt-Nachmais et al. (2015) and Sheperis et al. (2010), the primary categories of validity include internal, external, content, construct, and criterion validity. Threats to the internal and external validity of this study were most likely present. Internal threats to validity could occur from participants not taking the survey seriously, not being truthful while answering the questions, or not comprehending the questions' intentions. In this study, the relevant instruments like IBM opioid misuse questionnaires and the Likert scale (Likert, 1932) for IBM survey minimized the validity threat and promote the reliability and validity of the study. Moreover, time parameters are utilized to address concerns related to the history or maturation threats issues, since they serve as a cross-sectional design strategy. Purposeful convenience sampling is a non-probability sampling method which is easy in constructing sampling frames unlike random sampling where there may be difficulty in constructing sampling frames (Frankfort-Nachmias & Nachmias, 2008).

Cronbach's alpha and statistical regression analyses were used to test reliability and ensure that errors related to internal risks to the sampling method are effectively controlled (Mertler et al., 2021; Multon & Coleman, 2013). Cronbach's alpha value of .70 or higher shows there is internal reliability of the measurement items (Mertler et al., 2021). My study was conducted using an online anonymous survey in a natural setting, which promotes external validity and enables suitable analysis of descriptive relationships and patterns between variables using primary data. Therefore, external threats to validity were not a problem in this study. Furthermore, the findings can be generalized to other populations and environments with comparable demographics (Frankfort-Nachmias et al., 2015; Mertler et al., 2021).

Construct Validity

According to Creswell (2014) and Trochim and Donnelly (2008), construct validity is the degree to which an instrument accurately measures the construct, or notion, that the researcher claims it measures. As such, determining construct validity is a matter of test validation (Peng & Mueller, 2004) and is connected to the suitability of the instrument a researcher employs (Creswell, 2014). Test validation is the setting for this suitability. When variables and measurements are not defined correctly by researchers, construct validity may be compromised (Creswell, 2014). As recommended by Peng and Mueller (2004) and Sawilowsky (2007), I performed factor analysis on the instrument to guarantee construct validity in this study. Additionally, I employed a validated instrument whose scale reliability analyses show that all the scales are either good or very good. However, I carried out a scale reliability analysis for the measures of the six variables to make sure the scales were equally appropriate for the population in this study (Lauriola, 2004; Williams, 2017).

Statistical Conclusion Validity

The correctness of inferences based on the suitability of the statistical power employed to conduct the analyses and the statistical assumptions of the studies are referred to as statistical conclusion validity (Creswell, 2014). This test responds to the query, “Does a relationship exist between the two variables?” (Drost, 2011, p. 115).

For researchers to be confident that the treatments and interventions they claim have an impact on an outcome are responsible for that outcome, it is crucial to demonstrate statistical conclusion validity in practice. According to Creswell (2014, p. 176), “Threats to statistical conclusion validity arise when experimenters draw incorrect inferences from the data due to insufficient statistical power or the violation of statistical assumptions.” These dangers can be reduced with careful planning and data analysis.

Researchers must utilize the proper statistical power for the sort of studies being done to guarantee the validity of statistical conclusions (Cohen, 1992). A Type II error, in which the researcher fails to reject the null hypothesis, might result from using insufficient statistical power for analysis (Cohen, 1992). Cohen (1992) referred to a power of .80 as conventional, which could reduce the possibility of a Type II error in the study.

Effect size is crucial for assuring statistical conclusion validity along with statistical power. Cohen (1992) distinguished three categories of effect sizes for multiple regression analyses: small (.02), medium (.15), and large (.35). Using a small effect size may cause the researcher to omit pertinent data from studies (Cohen, 1992), which could prevent the researcher from detecting a pattern in the data even if it is present (Creswell, 2014). However, adopting a large effect size may cause the researcher to include irrelevant data in studies (Cohen, 1992; Williams, 2017), which could result in the researcher finding significant results even though the data do not truly support the hypothesis of the pattern being examined (Creswell, 2014). I picked a medium effect size to reduce the likelihood of correctly discovering significant associations in this investigation.

Ethical Permission, Concerns, and Procedures

When analyzing human subjects, ethical considerations are frequently quite important. According to Teachers College Columbia University, a researcher’s ethical responsibility to participants includes being aware of any potential hazards associated with using human subjects in study. According to this ethical obligation, researchers must appropriately recognize, mitigate, and disclose any potential damage or discomfort that may impact participants (U.S. Department of Health and Human Services [DHHS], 2009). Therefore, the least level of risk to human participants should be sought after.

According to the beneficence principle of the Belmont report, these negative effects are classified as hazards and ought to be kept to a minimum. Social risk, psychological injury, economic risk, and bodily harm are the four categories of possible risk that need to be considered (Teachers College Columbia University, n.d.). The danger to the human participants in this study was very minimal. The survey retrieved anonymous data through online-based questionnaires. The cooperating organization was concealed, and ethical standards were upheld without breaking any HIPAA rules. Additionally, in accordance with Walden University policy, clearance from the Walden Institutional Review Board (IRB) was requested and the Walden's University IRB approval number was 07-24-23-1023227 before recruitment of participant via distributing flyers and anonymous online-based collecting data from respondents. Also, I obtained ethical clearance and recruitment authorization for online-based survey from the organization in Nigeria for data collection.

An implied consent form information was made available to participants participating in the online-based survey to maintain complete anonymity. Each participant for the online-based survey read the implied consent information and agreed before the completion of survey. Participants were advised to print or save copies of the informed consent for future reference. The implied consent form informed every prospective participant about their right to withdraw from the study at any time and that the data they provided would be kept private and secured on a password-protected computer.

Treatment and Storage of Data

There are two methods of entering dataset in SPSS namely manual entry and importing from other file types [such as Microsoft excel, Strata, SAS, CSV data] (Buxton and Cornish, 2007). According to Buxton and Cornish (2007), the handling of numeric variables by SPSS is substantially better than the handling of string variables (data entered as text). Therefore, it is a good idea to enter any questions that ask for categorical replies (such as yes/no/don’t know, male/female, etc.) in Excel as numeric data (codes) rather than text if you want to transfer data from Excel to SPSS (Buxton and Cornish, 2007). For example, I coded “No” as 0 and “Yes” as 1. Also, I coded gender identity Male as 1 and Female as 2 in the SPSS. Before data was imported into SPSS, I organized the data in Excel such that answers from various respondents are shown in distinct rows and answers to various questions appear in different columns (Buxton & Cornish, 2007). For instance, the responses from the fifth person were placed in the fifth row of the data (ignoring the column titles), while the answers to the third question (from everyone) were placed in the third column (Buxton & Cornish, 2007). All data gathering uploaded into Microsoft excel was kept securely on my personal computer, and any access to it was granted only with a two-way authentication password for security measures. One password was for logging on to the personal computer and the other for safe data accessibility to avoid jeopardizing the confidential information and after being entered into Microsoft excel, then I transferred data from excel to SPSS software version 28.

After importing the data into SPSS, I carefully examined and cross-checked the datasets on the data view and variable view to see if all the datasets are correct. I started to explore the data for my study analysis. The datasets imported into SPSS will be kept for five years in my secure personal computer. At that point, I will destroy the raw data and SPSS files after 5 years in accordance with the Walden University regulation.

Summary

This study's research design was a cross-sectional correlational research design. The advantage of the correlational design is determining the degree of association between two or more variables (Wang & Cheng, 2020). The cross-sectional correlation design is excellent for social science research. It incorporates data collecting through surveys and questionnaires, enabling researchers to analyze one group or area at a time in a natural context (Frankfort-Nachmias & Nachmias, 2008; John, 2021; Sheperis et al., 2010). I recruited university students (males and females) who fitted the inclusion requirements and are between the ages of 18 and 25 using a purposeful convenience sampling method. A purposeful convenience sampling allows for the quick collection of data from eligible participants based on their convenience, accessibility, and personal experience (Frankfort-Nachmias et al., 2015; John, 2021).

The sample size is crucial in assessing the validity and reliability of the study's findings and their possible generalizability (Frankfort –Nachmias et al., 2015). The G*Power program was utilized to calculate effect sizes and visually present the outcomes of power studies (Faul et al., 2009).

The instrumentation for the study included a consent form, demographic questions, and IBM questionnaires using five-scale Likert measurement. The independent variables are the three IBM constructs; attitude (experiential and instrumental), perceived norms (injunctive and descriptive), and personal agency. The dependent variable is nonmedical prescription opioid use, and independent variables include (perceived control and self-efficacy). Age, gender, and educational level are the controlling variables. The IBM questionnaires using five-scale Likert measurement reduced the validity threat and supported the study's reliability and validity.

I conducted preliminary analyses to determine if all assumptions of multiple linear regression were met and no violations existed. I evaluated reliability using Cronbach's alpha analysis and statistical regression analysis to ensure that mistakes relating to internal risks to the sampling procedure were properly handled (Mertler et al., 2021). Finally, the analysis technique involved two phases (descriptive statistics, and multiple linear regression) which were used to examine the predictive relationship between variables and the hypotheses of the three research questions.

Chapter 4: Results

In this study, I quantitatively examined the predictive relationship between the three constructs of IBM, demographic factors (age, gender, educational level) as significant determinants of nonmedical prescription opioid use among young adults in Nigeria. My goal was to ascertain the relationship between intents, feelings, and moods associated to NMPOU among young people in Nigeria between the ages of 18 and 25, utilizing the three IBM constructs (attitudes, perceived norms, and personal agency) that may be contributing to the prevalence of opioid misuse and addiction. The results of the data analysis discussed in this chapter may be used to develop policies, provide additional insight into opioid management, increase procedures for standard of care in our society, and improve the sociobehavioral values of young adults between the ages of 18 and 25.

The data employed for this study were obtained from an online-based anonymous survey conducted at a fully accredited institution of higher education in Nigeria. The survey included a demographic form questionnaire and an IBM questionnaire to assess primary outcomes and latent constructs. The study was guided by the formulation of research questions and hypotheses, which are as follows:

RQ1: Is there an association between attitudes (instrumental and experiential]), as measured by the 5-point Likert scale, and nonmedical prescription opioid use, as measured by the IBM questionnaires, controlling for age, gender, and educational level.

$H_0 1$: There is no relationship between attitudes [instrumental and experiential] (measured by the 5-point Likert scale) and nonmedical prescription opioid use (measured by the IBM questionnaires), controlling for age, gender, and educational level.

H_a1: There is a relationship between attitudes [instrumental and experiential] (measured by the 5-point Likert scale) and nonmedical prescription opioid use (measured by the IBM questionnaires), controlling for age, gender, and educational level.

RQ2: Is there an association between perceived norms [descriptive, subjective, and injunctive] (measured by the 5-point Likert scale) and nonmedical prescription opioid use (measured by the IBM questionnaires), controlling for age, gender, and educational level.

H_02: There is no relationship between perceived norms [descriptive, subjective, and injunctive] (measured by the 5-point Likert scale), and nonmedical prescription opioid use (measured by the IBM questionnaires), controlling for age, gender, and educational level.

H_a2: There is a relationship between perceived norms [descriptive, subjective, and injunctive] (measured by the 5-point Likert scale) and nonmedical prescription opioid use (measured by the IBM questionnaires), controlling for age, gender, and educational level.

RQ3: Is there an association between personal agency [perceived control and self-efficacy] (measured by the 5-point Likert scale) and nonmedical prescription opioid use (measured by the IBM questionnaires), controlling for age, gender, and educational level.

H_03: There is no relationship between personal agency [perceived control and self-efficacy] (measured by the 5-point Likert scale) and nonmedical prescription opioid use (measured by the IBM questionnaires), controlling for age, gender, and educational level.

H_a3: There is a relationship between personal agency [perceived control and self-efficacy] (measured by the 5-point Likert scale) and nonmedical prescription opioid use (measured the IBM questionnaires), controlling for age, gender, and educational level.

Data Collection

The IRB permission for my research at Walden University was acquired on July 24, 2023, with the approval number 07-24-23-1023227. The data collection process involved the retrieval of information using an anonymous online survey administered at a university. This survey was conducted within a specified timeframe, spanning from July 31, 2023, to August 31, 2023. Participants were university students aged 18 to 25 years who satisfied the inclusion criteria successfully and filled out the online survey by accessing the provided hyperlink in the recruitment flyer. Electronic data collection instruments consist of a demographic form, an implied consent form, and IBM questionnaires for primary outcomes and latent constructs. A total of 188 participants participated in the survey, and I ensured strict adherence to the methodological protocols and guidelines outlined in Chapter 3.

Results

The outcomes and discussions of statistical analyses performed in accordance with the nature of the analyses are provided in this section. First, I performed preliminary analyses to assess the assumptions of multicollinearity, outliers, normality, linearity, homoscedasticity, and independence of residuals. Second, I employed descriptive statistics to analyze the demographics of the study participants. Third, I conducted multiple linear regression utilizing the enter method to examine the correlation matrix between the dependent and independent variables. In addition, Pearson's correlation coefficient test to determine if multicollinearity between variables existed.

Descriptive Analysis

The frequency distribution of the participants' demographic categories can be seen in Table 2. Of the total sample size of 188 participants aged 18 to 25 years who completed the survey in its entirety, 91 participants (48.4%) were male, whereas 97 participants (51.6%) were female. The study examined the educational levels of participants based on categorized educational levels. The findings revealed that freshmen (100 level) accounted for 15.96% of the sample (*n* = 30). The highest percentage, 37.23% (*n* = 70), was observed among sophomores (200 level). Juniors (300 level) constituted 20.21% of the sample (*n* =38), and seniors (400 level) accounted for 26.60% (*n* = 50). Notably, there were no participants at the master's degree or PhD level.

The frequency data for the dependent and independent variables are indicated in Table 3. The dependent variable survey responses are grouped into five categories as everyday, someday, once a month, not at all and quit following all participants confirmed having heard or seen opioids, resulting in a 100%. The participants provided information regarding the frequency of their engagement in nonmedical prescription opioid use (NMPOU), which was categorized into five groups. The category of everyday responses consisted of 58 participants, accounting for 30.80% of the total. The category of someday responses had the highest number of participants, with 87 individuals representing 46.20% of the total while the once-a-month category had 43 participants, making up 23.00% of the total. There were no recorded responses for the categories "not at all" and "quit" within the sample responses while the independent variables comprise of responses in the Likert scale (strongly agree, agree, neutral, disagree, and disagree).

Table 2

Frequency Distribution of Participants' Demographics (N = 188)

Variable	Category	*n*	%
Age	18 to 25 years	188	100.0
Gender	Male	91	48.4
	Female	97	51.6
Educational level	Freshmen (100 level)	30	15.96
	Sophomore (200 level)	70	37.23
	Junior (300 level)	38	20.21
	Senior (400 level)	50	26.60
	Master's degree (500 level)	0	0
	PhD degree (600 level)	0	0

Table 3

Dependent and Independent Variables' Responses (N = 188)

Variable	Category	*n*	%
Frequency of opioid use			
Have you heard of or seen opioids before this study?	Yes	188	100.0
	No	0	0
If you answered 'yes' to have heard or seen opioids, how often do you now engage in nonmedical prescription opioid use NMPOU?	Everyday	59	31.38
	Someday	87	46.28
	Once a month	42	22.34
	Not at all	0	0.0
	Quit	0	0
Attitude			
Experiential			
Feelslikepills	Strongly agree	94	50.0
	Agree	92	48.94
	Neutral	1	0.53
	Disagree	1	0.53
	Strongly disagree	0	0.0
Feelsbeta	Strongly agree	72	38.3
	Agree	113	60.11
	Neutral	1	0.53
	Disagree	1	0.53
	Strongly disagree	1	0.53
Thinksbeta	Strongly agree	73	38.83
	Agree	111	59.04
	Neutral	3	1.60
	Disagree	1	0.53
	Strongly disagree	0	0.0
Feelslonely	Strongly agree	70	37.23
	Agree	116	61.70
	Neutral	1	0.53
	Disagree	1	0.53
	Strongly disagree	0	0.0
Feelsstrong	Strongly agree	77	40.96
	Agree	108	57.45
	Neutral	3	1.60
	Disagree	0	0.0
	Strongly disagree	0	0.0
Instrumental			
Feelstasty	Strongly agree	75	39.89
	Agree	110	58.51
	Neutral	2	1.07
	Disagree	1	0.53
	Strongly disagree	0	0.0
NMPOUSmell	Strongly agree	81	43.09
	Agree	105	55.85
	Neutral	2	1.06
	Disagree	0	0.0
	Strongly disagree	0	0.0

Variable	Category	*n*	%
NMPOUHipQuit	Strongly agree	63	37.51
	Agree	123	65.43
	Neutral	1	0.53
	Disagree	1	0.53
	Strongly disagree	0	0.0
NMPOUAlt	Strongly agree	74	39.56
	Agree	111	59.04
	Neutral	3	1.60
	Disagree	0	0.0
	Strongly disagree	0	0.0
Feelsociable	Strongly agree	85	45.21
	Agree	102	54.26
	Neutral	0	0.0
	Disagree	1	0.53
	Strongly disagree	0	0.0
Perceived Norm			
Injunctive			
NMPOAccpt	Strongly agree	91	48.40
	Agree	94	50.0
	Neutral	3	1.60
	Disagree	0	0.0
	Strongly disagree	0	0.0
TpBemater	Strongly agree	44	23.53
	Agree	60	32.09
	Neutral	1	0.53
	Disagree	81	43.32
	Strongly disagree	2	1.0
Subjective			
FRpPosOp	Strongly agree	64	34.04
	Agree	122	64.89
	Neutral	1	0.53
	Disagree	1	0.53
	Strongly disagree	0	0.0
FRnNegOp	Strongly agree	79	42.02
	Agree	107	56.91
	Neutral	2	1.06
	Disagree	0	0.0
	Strongly disagree	0	0.0
OKFrTak	Strongly agree	83	44.15
	Agree	102	54.26
	Neutral	2	1.06
	Disagree	0	0.0
	Strongly disagree	1	0.53
TkPCloNMPO	Strongly agree	57	30.32
	Agree	128	68.09
	Neutral	3	1.60
	Disagree	0	0.0
	Strongly disagree	0	0.0
TkiPoDrE	Strongly agree	91	48.0
	Agree	94	50.0
	Neutral	3	1.60
	Disagree	0	0.0
	Strongly disagree	0	0.0

Variable	Category	*n*	%
Descriptive			
NMPOCeleb	Strongly agree	88	46.81
	Agree	96	51.06
	Neutral	4	2.13
	Disagree	0	0.0
	Strongly disagree	0	0.0
PeSpdTime	Strongly agree	65	34.57
	Agree	117	62.23
	Neutral	6	3.19
	Disagree	0	0.0
	Strongly disagree	0	0.0
PeAttnsekers	Strongly agree	70	37.3
	Agree	115	61.17
	Neutral	3	1.60
	Disagree	0	0.0
	Strongly disagree	0	0.0
PeOrgdz	Strongly agree	65	34.57
	Agree	120	63.83
	Neutral	3	1.60
	Disagree	0	0.0
	Strongly disagree	0	0.0
YofeelOrgdz	Strongly agree	76	40.64
	Agree	109	58.29
	Neutral	2	1.60
	Disagree	0	0.0
	Strongly disagree	1	0.53
Personal Agency			
Perceived Behavioral Control			
TakOpEvrwy	Strongly agree	84	44.68
	Agree	99	52.66
	Neutral	4	2.13
	Disagree	1	0.53
	Strongly disagree	0	0.0
NMPOAffdable	Strongly agree	95	50.53
	Agree	97	48.40
	Neutral	2	1.06
	Disagree	0	0.0
	Strongly disagree	0	0.0
Self-Efficacy			
HardStop	Strongly agree	91	48.40
	Agree	94	50.00
	Neutral	2	1.06
	Disagree	1	0.53
	Strongly disagree	0	0.0
HardToObt	Strongly agree	73	38.83
	Agree	110	60.64
	Neutral	1	0.53
	Disagree	0	0.0
	Strongly disagree	0	0.0

Preliminary Analyses

The reliability of the 27 survey items employed for the IBM constructs and dependent variable (frequency of opioid use) measurements was confirmed by Cronbach's alpha of .855. The Cronbach's alpha on the standardized items was .869. Afterwards, I computed the 27 standardized items used to assess the three IBM constructs using transform tab in SPSS, the Cronbach's alpha of the attitude reliability was .843 *(M = 1.6122; SD = .27771).* The Cronbach's alpha of the perceived norm reliability was .843 *(M = 1.7035; SD = .30955*). Cronbach's alpha of the personal agency reliability was .843 *(M = 1.5612; SD = .36598).*

Table 4

Summary Item Statistics

	M	Minimum	Maximum	Range	Maximum / Minimum	Variance	No. of Items
Item means	1.656	1.505	2.660	1.154	1.767	.047	27

Testing of Statistical Assumptions

The research questions were examined through regression analysis. I employed assumption testing to ascertain the validity of the data, as multiple linear regression necessitates the fulfillment of certain assumptions. These assumptions include multicollinearity, outliers, normality, linearity, homoscedasticity, and independence of residuals.

Multicollinearity

Field (2013) proposed that the evaluation of multicollinearity should be performed using SPSS collinearity diagnostics by monitoring the VIF, which should be less than 10. The VIF value of every predictor was found to be less than 10, which suggests that there is no existence of multicollinearity (see Table 5).

Table 5

Collinearity Diagnostics – Variance Inflation Factor (Multicollinearity)

Model	Variable	Collinearity statistics	
		Tolerance	VIF
1	Attitudes	.532	1.881
	Perceived Norms	.418	2.394
	Personal Agency	.501	1.997
	Gender	.912	1.096
	Educational level	.952	1.051

Note. Dependent variable: Frequency of Opioid Use (NMPOU). Age (18 to 25 years old) remained constant.

Independence of Residuals

The Durbin-Watson test was performed and resulted in a value of 1.482, indicating the confirmation of the assumption of the independence of residuals (see Table 8). The Durbin-Watson statistic is a measure of autocorrelation in a regression analysis and tests the null hypothesis that the residuals are not linearly autocorrelated. It is bounded between 0 and 4, and typically, a value of 2.0 indicates lack of autocorrelation is observed in the sample (Madden, 2016). Values from 0 to less than 2 indicate positive autocorrelation while values from 2 to 4 indicate negative autocorrelation (Madden, 2016; Tabachnick & Fidell, 2007). Histogram and scatterplots in SPSS were used to validate the assumptions of normality, linearity, and homoscedasticity (see Figures 2–7). The residuals analysis was utilized to determine any error independence. These analyses revealed that all of the assumptions for multiple linear regression analysis were met, and no violations were noted.

Figure 2

Histogram of the Residuals

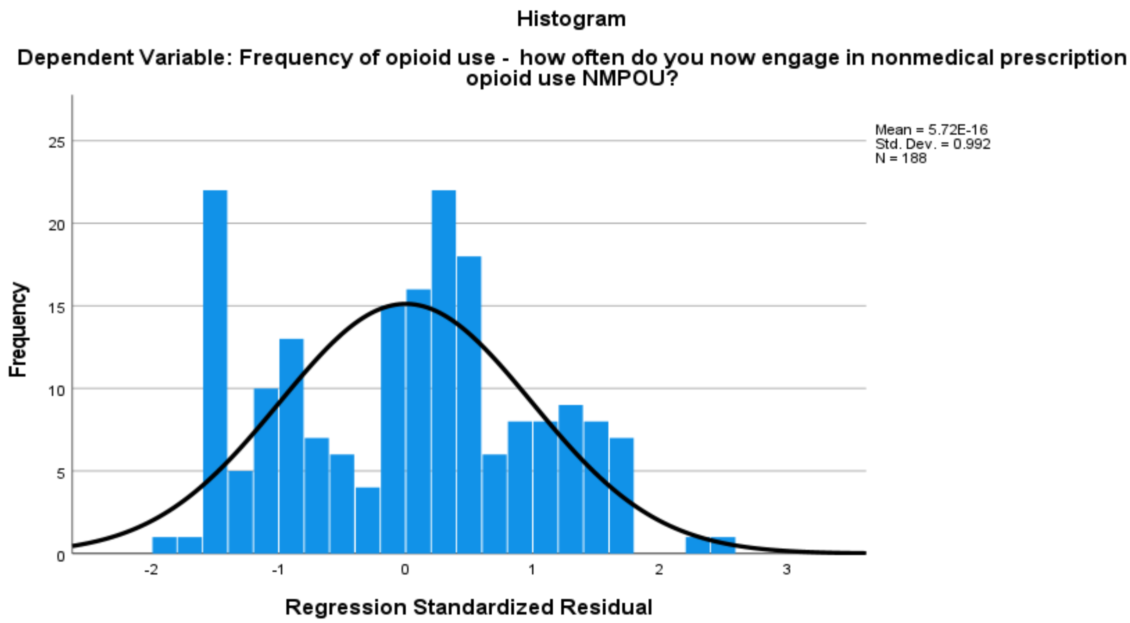


Figure 3

Assessing Normality

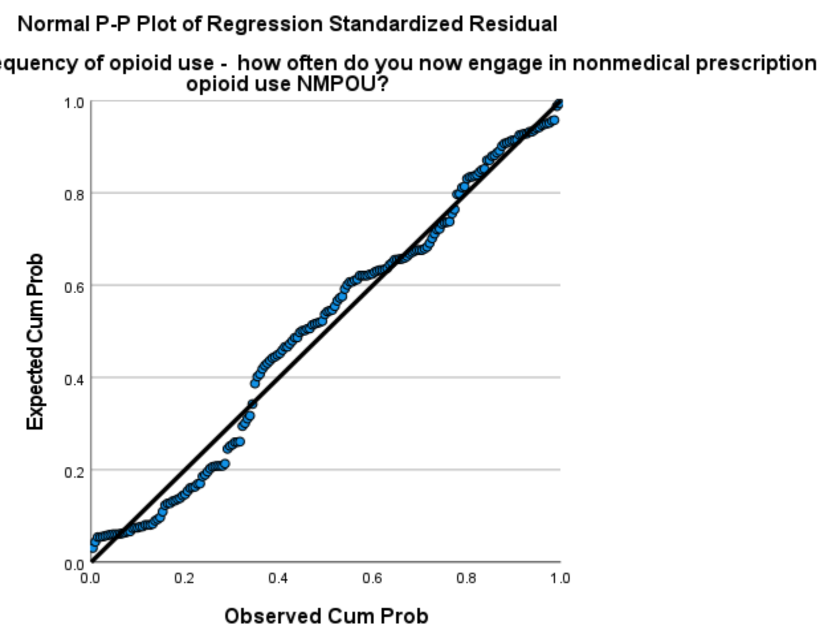


Figure 4

Assessing Linearity and Homoscedasticity

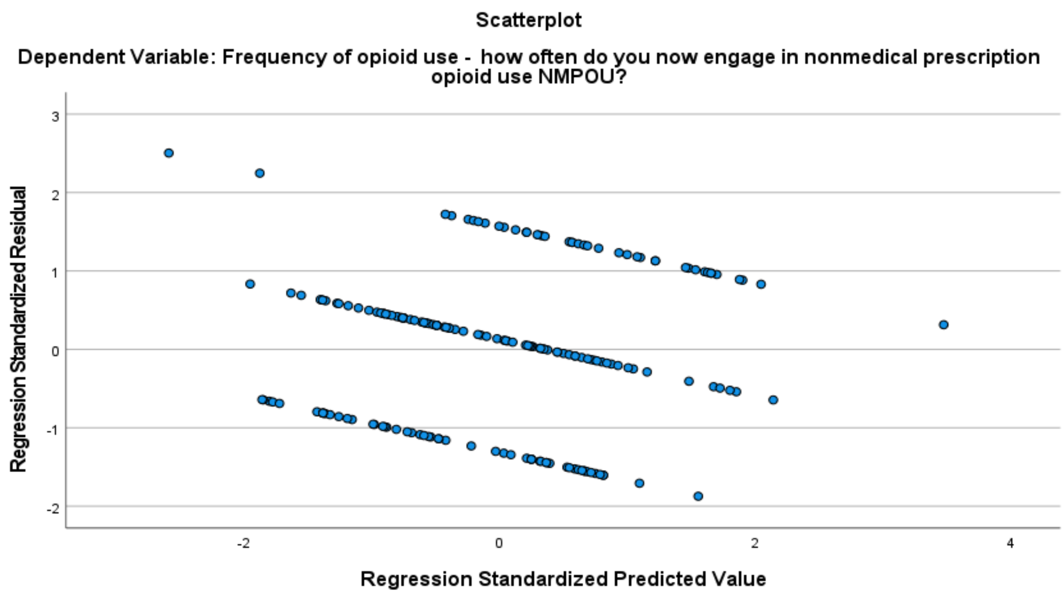


Figure 5

Partial Regression Plot for Attitudes: Assumptions Met

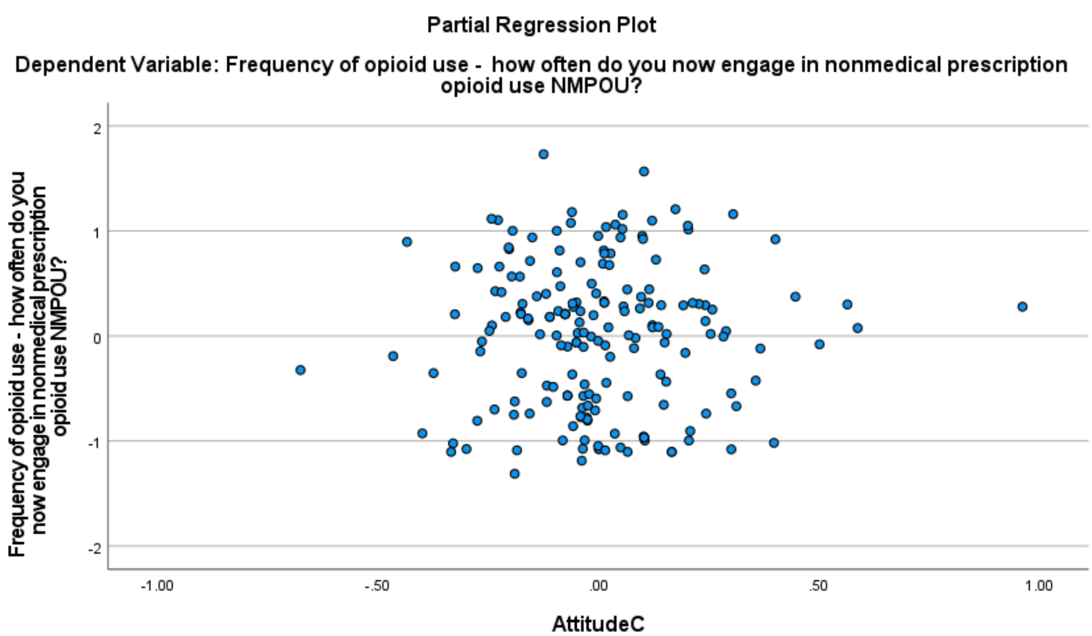


Figure 6

Partial Regression Plot for Perceived Norms: Assumptions Met

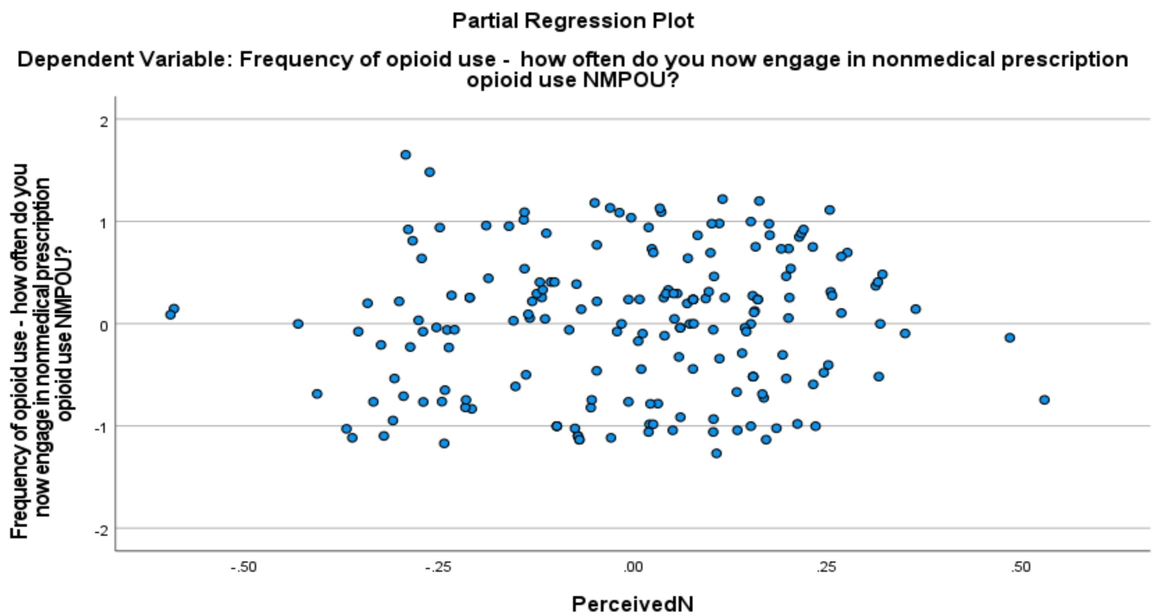
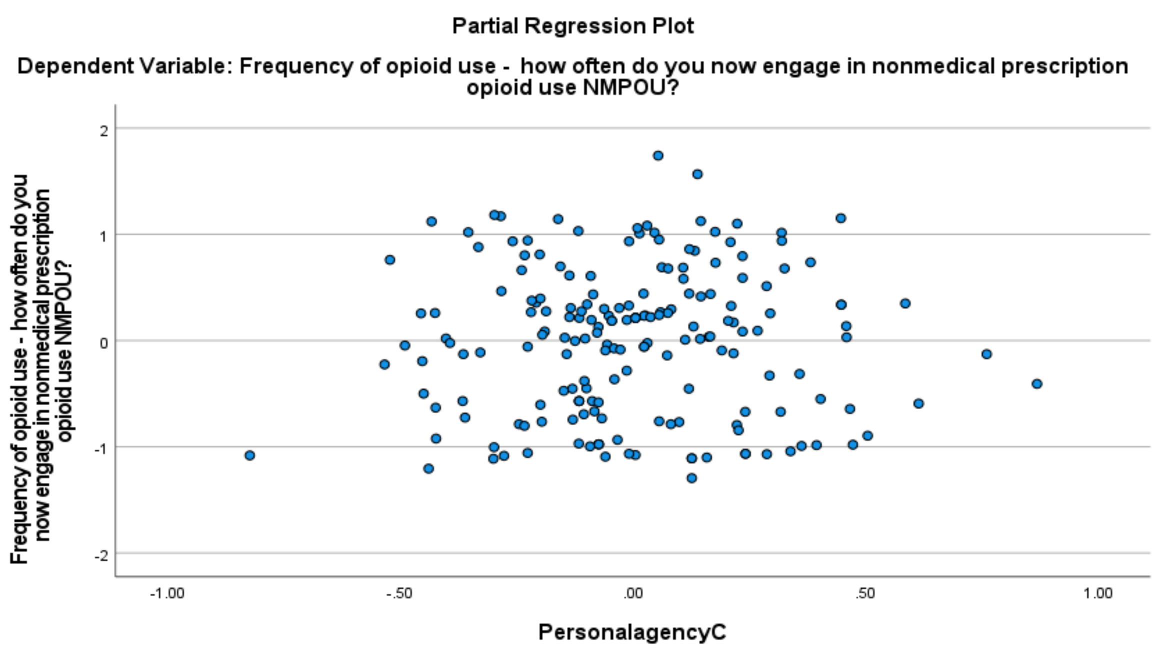


Figure 7

Partial Regression Plot for Personal Agency: Assumptions Met



Factor Analysis

Factor analysis was conducted in order to compute the correlation matrix and ensure the construct validity of the 27 items utilized in this study. Factor analysis was conducted to assess various statistical measures, including the component correlation matrix, communalities, Kaiser-Meyer-Olkin (KMO) measure, Bartlett's test, total variance, and the rotated component matrix. The KMO and Bartlett test examined the suitability of combining all available data for analysis. According to Reddy and Kulshrestha (2019), a KMO value more than 0.5 and a significance level below 0.05 for the Bartlett's test indicate a significant connection within the dataset. The results of the KMO test indicated a KMO value of 0.854, while the Bartlett test demonstrated a significance level below 0.01. These findings collectively suggest the presence of a significant correlation within the dataset (see Table 6).

Table 6

KMO and Bartlett's Test

Measure	Value
Kaiser-Meyer-Olkin Measure of Sampling Adequacy	.854
Bartlett's Test of Sphericity	
Approximate chi-square	1122.092
df	351
Sig.	<.001

Main Statistical Analysis

I conducted multiple linear regression analysis using the Enter method in SPSS for this study. The study excluded the age of the participants in the regression analysis, and it was coded as 2 in the SPSS, as it aimed to predict the association between the independent variables, and dependent variable, specifically among young adults aged 18 to 25 years old. For the case of sex, I created a dichotomy exclusive of transgender categories and I recoded it to one variable: "GenderID,” a dummy variable transformed into a “1 to a 2” dichotomy where 1 = male and 2 = female. For the educational level, I computed the survey responses from the six categories, where 1 is freshman level, 2 is sophomore level, 3 is junior level, 4 is senior level, 5 is master’s level, and 6 is Ph.D. level using the transform menu in the SPSS. The regression analysis examined the strength of the correlations between the three IBM constructs (attitude, perceived norm, and personal agency) and nonmedical prescription opioid usage while controlling for age, gender, and educational level (RQ1 – RQ3). Preliminary analyses were conducted to assess the assumptions of multicollinearity, normality, outliers, linearity, homoscedasticity, and independence of residuals. Hence, all assumptions for multiple linear regression analysis were met and no violations were observed during assumption testing (see Figures 2–7).

Research Questions Results

RQ1: Is there an association between attitudes (instrumental and experiential]), as measured by the 5-point Likert scale, and nonmedical prescription opioid use, as measured by the IBM questionnaires, controlling for age, gender, and educational level.

$H_0$1: There is no relationship between attitudes [instrumental and experiential] (measured by the 5-point Likert scale) and nonmedical prescription opioid use (measured by the IBM questionnaires), controlling for age, gender, and educational level.

*H*a1: There is a relationship between attitudes [instrumental and experiential] (measured by the 5-point Likert scale) and nonmedical prescription opioid use (measured by the IBM questionnaires), controlling for age, gender, and educational level.

Statistical Results of RQ1

I performed descriptive statistics and multiple linear regression to determine predictive relationships between attitudes and NMPOU while controlling for age, gender, and educational level. The coefficient of determination (R^2) suggests that approximately 11% of the total variability of outcome variable was explained by attitudes, gender, and educational level. The results of the multiple linear regression were significant, $R^2 = .108$, $F(3,184) = 7.404$, $p < .001$. The predictor variable (attitude) in this model was not significant; $\beta = .113$, $t = 1.565$, $p = .119$. The controlling variables were significant, with gender ($\beta = .238$, $t = 3.340$, $p = .001$) providing a higher contribution to the model than educational level ($\beta = .188$, $t = 2.653$, $p = .009$). In RQ 1 results, not all of the results support the hypotheses, attitude ($p = .119$) was not significant, while gender ($p = .001$) and educational level ($p = .009$) were statistically significant in the model. Table 7 depicts the descriptive statistics. Table 8 depicts the regression summary. Table 9 depicts the summary of ANOVA. Table 10 depicts beta scores. The regression formula is $Y =$ .569 + .297 (attitudes) + .346(Gender) + .131(educational level)

Table 7

Descriptive Statistics for RQ1

Variable	*M*	*SD*	*N*
Frequency of Opioid Use	1.91	.729	188
Attitude	1.6122	.27771	188
Age	2.000	.0000	188
Gender	1.52	.501	188
Educational levels	2.5745	1.04946	188

Table 8

Summary of Regression Analysis for RQ1

Model	*R*	R^2	Adjusted R^2	*SE* of estimate	Durbin-Watson
1	.328	.108	.093	.695	1.452

Note. Predictor: (constant), attitudes, gender, educational level; Dependent variable: frequency of opioid use (NMPOU).

Table 9

Summary of ANOVA for RQ1

Model		*SS*	*df*	*MS*	*f*	sig
1	Regression	10.714	3	3.571	7.404	<.001
	Residual	88.749	184	.482		
	Total	99.463	187			

Note. Dependent variable: Frequency of Opioid Use (NMPOU)

Table 10

Summary of Coefficients for RQ1

Variable	B	*SE*	Beta	*t*	Sig.	95% confidence interval for B	
						Lower bound	Upper bound
Constant	.569	.360		1.581	.116	-.141	1.280
Attitudes	.297	.190	.113	1.565	.119	-.078	.672
Gender	.346	.104	.238	3.340	.001	.142	.551
Educational L	.131	.049	.188	2.653	.009	.033	.228

Note. Dependent variable: Frequency of Opioid Use (NMPOU).

RQ2: Is there an association between perceived norms [descriptive, subjective, and injunctive] (measured by the 5-point Likert scale) and nonmedical prescription opioid use (measured by the IBM questionnaires), controlling for age, gender, and educational level.

$H_0$2: There is no relationship between perceived norms [descriptive, subjective, and injunctive] (measured by the 5-point Likert scale), and nonmedical prescription opioid use (measured by the IBM questionnaires), controlling for age, gender, and educational level.

H_a2: There is a relationship between perceived norms [descriptive, subjective, and injunctive] (measured by the 5-point Likert scale) and nonmedical prescription opioid use (measured by the IBM questionnaires), controlling for age, gender, and educational level.

Statistical Results of RQ2

I performed descriptive statistics and multiple linear regression to determine predictive relationships between perceived norms and NMPOU while controlling for age, gender, and educational level. The coefficient of determination (R^2) suggests that approximately 12% of the total variability of outcome variable was explained by perceived norms, gender, and educational level. The results of the multiple linear regression were significant, $R^2 = .117$, $F(3,184) = 8.164$, $p < .001$. All the predictors in this model were significant with outcome variable, with perceived norms ($\beta = .157$, $t = 2.124$, $p = .035$), gender ($\beta = .216$, $t = 2.987$, $p = .003$), and educational level ($\beta = .200$, $t = 2.818$, $p = .005$). Gender has a higher contribution to the model than other variables. Table 11 depicts the descriptive statistics. Table 12 shows the regression summary. Table 13 depicts the summary of ANOVA. Table 14 shows the beta scores. The regression formula is Y = .444 + .370(perceived norms) + .315(gender) + .139(educational level). In RQ 2 results, all of the predictors in this model were statistically significant with the outcome variable. As hypothesized, perceived norms (descriptive, subjective, and injunctive) were associated with nonmedical prescription opioid use ($\beta = .157$, $t = 2.124$, $p = .035$). These findings remained consistent even after considering the influence of covariates such as gender, and educational level. Hence, the null hypotheses were rejected.

Table 11

Descriptive Statistics for RQ2

Variable	*M*	*SD*	*N*
Frequency of Opioid Use	1.91	.729	188
Perceived norms	1.7035	.30955	188
Age	2.000	.0000	188
Gender	1.52	.501	188
Educational levels	2.5745	1.04946	188

Table 12

Summary of Regression Analysis for RQ2

Model	*R*	R^2	Adjusted R^2	*SE* of estimate	Durbin-Watson
1	.343	.117	.103	.691	1.493

Note. Predictor: (constant), attitudes, gender, educational level; Dependent variable: frequency of opioid use (NMPOU)

Table 13

Summary of ANOVA for RQ2

Model		*SS*	*df*	*MS*	*f*	Sig.
2	Regression	11.685	3	3.895	8.164	<.001
	Residual	87.778	184	.477		
	Total	99.463	187			

Note. Dependent variable: Frequency of Opioid Use (NMPOU); Predictors: (constant), perceived norms, educational level, gender.

Table 14

Summary of Coefficients for RQ2

Variable	B	*SE*	Beta	*t*	sig	95% confidence interval for B	
						Lower bound	Upper bound
Constant	.444	.344		1.293	.198	-.234	1.123
Perceived N	.370	.174	.157	2.124	.035	.026	.714
Gender	.315	.105	.216	2.987	.003	.107	.523
Educational L	.139	.049	.200	2.818	.005	.042	.236

Note. Dependent variable: Frequency of Opioid Use (NMPOU).

RQ3: Is there an association between personal agency [perceived control and self-efficacy] (measured by the 5-point Likert scale) and nonmedical prescription opioid use (measured by the IBM questionnaires), controlling for age, gender, and educational level.

*H_0*3: There is no relationship between personal agency [perceived control and self-efficacy] (measured by the 5-point Likert scale) and nonmedical prescription opioid use (measured by the IBM questionnaires), controlling for age, gender, and educational level.

*H_a*3: There is a relationship between personal agency [perceived control and self-efficacy] (measured by the 5-point Likert scale) and nonmedical prescription opioid use (measured the IBM questionnaires), controlling for age, gender, and educational level.

Statistical Results of RQ3

I performed descriptive statistics and multiple linear regression to determine predictive relationships between personal agency and NMPOU while controlling for age, gender, and educational level. The coefficient of determination (R^2) suggests that approximately 11% of the total variability of outcome variable was explained by personal agency, gender, and educational level. The results of the multiple linear regression were significant, $R^2 = .108$, $F(3,184) = 7.461$, $p < .001$. The predictor variable (personal agency) in this model was not significant; $\beta = .116$, $t = 1.613$, $p = .108$. The controlling variables were significant, with gender ($\beta = .235$, $t = 3.285$, $p = .001$) providing a higher contribution to the model than educational level ($\beta = .183$, $t = 2.605$, $p = .010$). In RQ 3 results, not all of the results support the hypotheses, personal agency (p = .108) was not significant, while gender ($p = .001$) and educational level ($p = .010$) were statistically significant in the model. Table 15 depicts the descriptive statistics. Table 16 depicts the regression summary. Table 17 depicts the summary of ANOVA. Table 18 depicts beta scores. The regression formula is Y = .702 + .232 (personal agency) + .342(Gender) + .127(educational level).

Table 15

Descriptive Statistics for RQ3

Variable	*M*	*SD*	*N*
Frequency of Opioid Use	1.91	.729	188
Personal Agency	1.5612	.36598	188
Gender	1.52	.501	188
Educational levels	2.5745	1.04946	188
Age	2.0000	.00000	188

Table 16

Summary of Regression Analysis for RQ3

Model	*R*	R^2	Adjusted R^2	*SE* of estimate	Durbin-Watson
1	.329	.108	.094	.694	1.461

Note. Predictors: (constant), personal agency, gender, educational level; Dependent variable: frequency of opioid use (NMPOU).

Table 17

Summary of ANOVA for RQ3

Model		SS	*df*	*MS*	*f*	Sig.
1	Regression	10.787	3	3.596	7.461	<.001
	Residual	88.676	184	.482		
	Total	99.463	187			

Note. Dependent variable: Frequency of Opioid Use (NMPOU).

Table 18

Summary of Coefficients for RQ3

Variable	B	*SE*	Beta	*t*	Sig.	95% confidence interval for B	
						Lower bound	Upper bound
Constant	.702	.290		2.424	.016	.131	1.274
Perceived Agency	.232	.114	.116	1.613	.108	.052	.515
Gender	.342	.104	.235	3.285	.001	.137	.547
Educational L	.127	.049	.183	2.605	.010	.031	.223

Note. Dependent variable: Frequency of Opioid Use (NMPOU).

Summary

In this chapter, I discussed the data collection and screening process, demographics, descriptive analyses, and research questions and hypotheses. The purpose of this study was to use a quantitative approach to determine which variables (i.e., attitudes, perceived norms, personal agency and demographic factors like gender, educational level, age as controlling variables) were associated with nonmedical prescription opioid use among young adults in Nigeria. Before conducting the primary statistical analysis, a preliminary analysis was performed to assess the reliability of the 27 survey items used for the IBM constructs and the dependent variable (frequency of opioid use for nonmedical purposes). This assessment was confirmed using Cronbach's alpha. The assumptions of multiple linear regression, including multicollinearity, outliers, normalcy, linearity, homoscedasticity, and independence of residuals, were examined, and evaluated. My study showed that all assumptions necessary for multiple linear regression analysis were met, and no instances of violation were observed.

I employed the Enter method of multiple linear regression. The age of the study participants was excluded from the regression analysis as the study aimed to predict the association between the independent variables and dependent variable specifically among young adults aged 18 to 25 years old. For the first and third research questions, although not all of the findings support my research hypotheses. Attitudes and personal agency are not significantly associated with nonmedical prescription opioid use but gender (with women being more likely than men to initiate opioid misuse), and educational level were statistically significant with nonmedical prescription use.

However, for the second research question, perceived norms, gender, and educational level were statistically significant with nonmedical prescription opioid use. There is a relationship between perceived norms (including descriptive, subjective, and injunctive norms), gender, educational level, and nonmedical prescription opioid usage among young adults in Nigeria. In chapter 5, I provided the interpretation of the study findings, an exploration of the study limitations, suggestions for future research, an examination of the implications for fostering positive social changes, and a comprehensive conclusion of the study.

Chapter 5: Discussion, Conclusions, and Recommendations

Many researchers have studied NMPOU, opioid misuse, opioid addiction, and associated risk behavior, but there remains a significant gap in the current literature regarding examining the individual-level factors that influence the prevalence, morbidity, and mortality rates of nonmedical prescription opioid use among young adults in Nigeria. The objective of this study focused on examining the predictive relationship between three constructs of the IBM (attitudes, perceived norms, and personal agency) and nonmedical prescription opioid use in young adults while controlling for age, gender, and educational level.

The theoretical framework of the study was Fishbein's IBM. The findings of this study offer a comprehensive framework that can guide future researchers, business executives, policymakers, public health professionals, community leaders, and school administrators in developing suitable health, social, and educational initiatives and tactics that effectively cater to the requirements of young adults in our society. These initiatives may include measures such as restricting the availability of prescriptions, disseminating information on improved pain management methods, and providing education on the dangers of nonmedical prescription opioid use to university students and other young adults aged 18 to 25 years, while discouraging recreational consumption.

The findings promote positive social change by enacting policies and laws that monitor nonmedical prescription opioids use in colleges and universities, prevent young adults aged 18 to 25 from obtaining nonmedical prescription opioids from street vendors, and eliminate opioid addiction by improving medication administration safety.

My study employed a cross-sectional methodology to quantitatively analyze primary data collection. Primary data was collected through an anonymous online survey of university students in Nigeria who met the specified inclusion criteria. My study examined the relationships between the three constructs of the IBM (attitude, perceived norms, and personal agency), demographic factors (age, gender, educational level), and nonmedical prescription opioid use among young adults aged 18 to 25 years old in Nigeria. The online survey data collection instrumentation consists of an implied consent form, demographic form, and IBM questionnaires for primary outcomes and latent constructs.

Interpretation of the Findings

As mentioned in Chapter 1, there is a significant gap in research on the health behavior determinants of opioid misuse and opioid addiction. The clandestine nature of opiate addiction and abuse hinders the identification of the individual-level contributing factors. Self-reported statistics from individuals who abuse or are addicted to opioids are frequently used to substantiate their cases. This study both confirms and offers novel insights into the findings discussed in the literature review. I found several statistically significant associations between the variables investigated. In RQ2, perceived norms, gender, and educational level (p = .035, .003, and .005, respectively) were revealed to be statistically significant predictors of the NMPOU.

Attitudes and personal agency were not statistically significant predictors of the NMPOU. I was unable to reject the null hypothesis in RQ1 and RQ3, even though gender and educational level both exhibited a significant connection with NMPOU. In this chapter, I interpret the key findings, discuss the study's limitations, provide recommendations, and discuss the implications and conclusions of this research study to address the problem of NMPOU among young adults in Nigeria.

Interpretation Related to Theoretical Framework

The theoretical framework of the study was Fishbein's IBM, which proposes the effectiveness of this model in predicting young adults' intention to engage in the targeted health behavior such as nonmedical prescription opioid use among young adults by assessing the model's three constructs (attitudes, perceived norms, and personal agency) to understand health behaviors and its determinants. A health behavior model investigates personal characteristics such as beliefs, motives, values, expectations, perceptions, and other cognitive elements; personality traits such as affective and emotional states and traits; and overt behavior patterns, actions, and habits related to health maintenance, restoration, and improvement (Alemayehu et al., 2021).

In a study using the IBM measurement survey and applied respondent-driven sampling in six towns situated along the key transport routes in Ethiopia, Alemayehu et al. (2019) evaluated the effectiveness of the IBM in predicting the intention of HIV at-risk subpopulations to engage in the health behavior of interest, namely early screening and treatment of sexually transmitted infections. This was done by measuring the model constructs (Experiential Attitude, Instrumental Attitude, Normative Influence, Perceived Control, and Self-efficacy) and assessing their ability to explain the study subjects' intention to adopt the desired health behavior. The Likert scale was used to measure respondents' answers to questions based on the IBM constructs and their desire to perform the health behavior of interest. Alemayehu et al. found that there is statistical significance between respondents' perceived control and study subjects' intention to get early screening and treatment services of sexually transmitted infection. This study revealed an association with perceived norms (descriptive, subjective, and injunctive) and nonmedical prescription opioid use, which further confirms Alemayehu et al.'s finding that respondents' perceived control and their intention to get early screening and treatment services for sexually transmitted infection will promote the desired health control.

Branscum and Lora (2017) utilized the IBM constructs to ascertain the key theory-driven factors that influence the extent to which low-income, Hispanic moms of 2- to 5-year-old children monitor their consumption of fruits and vegetables. Their study sample consisted of 238 participants and their findings showed that intentions significantly predicted maternal monitoring of fruit and vegetables consumption (5.3% of the variance explained) and autonomy significantly predicted intentions (33.1% of the variance explained). My study findings showed that the perceived norms (intentions) have a strong correlation with NMPUO among young adults. Both studies demonstrated how an individual's perceived norms (descriptive, subjective, and injunctive) can aid individuals in discerning socially acceptable and inappropriate health behavior.

Martinez (2017) used the IBM to examine the relationship between young adults' intention and e-cigarette use behavior, as well as their attitude toward e-cigarettes, perceived norms regarding e-cigarette use, and perceived ability to use e-cigarettes. An analysis of the influence of the IBM constructs on adult e-cigarette usage can provide insights into the relative importance of specific individual-level factors in determining usage. Assessing whether the adoption of e-cigarettes is primarily motivated by attitudes rather than norms, for example, will facilitate the development of health campaign messages that are more effective in preventing their use among young adults aged 18 to 25. Martinez discovered a negative correlation between young individuals' pleasant emotions, perceived advantages, and normative attitudes regarding e-cigarettes, and their intention to cease using them. This, in turn, increased the chance of their present e-cigarette usage. Young individuals who saw greater benefits and experienced good emotions were less likely to perceive risks connected with e-cigarettes. Consequently, they were more likely to now use e-cigarettes. These findings suggest addressing the high perceived advantages and low risk perceptions of e-cigarettes among young adults, communication, educational, and policy methods should emphasize the health risks associated with e-cigarette use. My study findings were consistent with this study and close the gap in this study by addressing the perceived norms and low risk perception of performing a desired health behavior. In my study, the perceived norms construct was statistically significant to the dependent variable, which indicates study participants' intention to perform desired health behavior such as indulging in taking nonmedical prescription opioid.

Interpretation Related to Previous Research

My findings that gender (with women being more likely than men to initiate opioid misuse), educational level, and perceived norms was related to nonmedical prescription opioid use at statistically significant levels is consistent with previous researchers who also found relationships between gender (Ashrafioun et al., 2017; Papazisis et al., 2018; Rougemont-Bucking et al, 2018; Wright & Ramirez, 2021), educational level (Bakhshale et al., 2019; Barnett et al., 2019; Cho et al., 2021; McCabe et al., 2017; Peck et al.,2019), perceived norms (Alemayehu et al., 2021; Branscum & Lora, 2017; Elliot & Jones, 2019; Jalali et al., 2020; Martinez, 2017; Reid et al., 2018; Rice & Klein, 2019), and nonmedical prescription opioid use among young adults. Previous researchers who have conducted studies on college students in the United States have found that those who have a history of using prescription drugs for medical purposes are more likely to engage in the use of opioids for nonmedical purposes (Johnston et al., 2014; Lord et al., 2009; McCabe, 2008; Weyandt et al., 2021).

According to Alemayehu et al. (2019), individuals' intention (perceived norms) toward an action and perceived control (personal agency) can make them develop stronger desire to perform the behavior, and they are more likely to perform the behavior successfully. My study was correlational in nature with the purpose to determine if there are predictive relationships between attitudes (instrumental and experiential), perceived norms (descriptive, subjective, and injunctive), personal agency (perceived control and self-efficacy) as measured by the 5-point Likert scale and nonmedical prescription opioid use (measured by the IBM questionnaires), controlling for age, gender, and educational level. Findings in my study indicated there were statistically significant relationships between perceived norms, gender (with women being more likely than men to initiate opioid misuse), educational level, and nonmedical prescription opioid use. Therefore, my study findings were consistent with previous literature that indicated that the perceived norms construct was statistically significant to the dependent variable using IBM construct and the Likert scale for measurement.

Bakhshale et al. (2019) investigated the relationship between negative affectivity and nonmedical opioid use in two subsamples of people with and without pain, as well as among racially and ethnically diverse young adults attending a large Southwestern State University. They solely explored the difficulties of emotion dysregulation and the relationship between negative affectivities. They discovered that focusing on the regulation of emotions could be an effective therapeutic approach to decrease the misuse of prescription opioids among college students who experience negative emotions.

My study examined the association between attitudes, perceived norms, and personal agency with nonmedical prescription opioid use among young adults while controlling for age, gender, and educational level. My study discovered a substantial relationship between respondents' perceived norms to engage in nonmedical prescription opioid usage among young adults. Although attitudes and personal agency did not statistically significant with nonmedical prescription opioids among young adults, but my study concluded that the injunctive norms reflect people's perceptions of what behaviors are approved or disapproved by others. Therefore, perceived norms (descriptive subjective, and injunctive,) appear to assist an individual in determining socially acceptable and inappropriate health behavior. Gender and educational level are two main demographic correlates observed in my hypotheses.

Reid et al. (2018) conducted a study aimed at investigating the predictive association between perceived norms (descriptive, subjective, and injunctive) and attitude with intentions to learn genomic sequencing results. Researchers found out injunctive norms are significantly associated with attitudes when ambivalence was high but seems unrelated when ambivalence was low. Furthermore, they concluded that descriptive and injunctive norms play major roles in genomic sequencing decisions. My study revealed statistical significance between perceived norms (descriptive, subjective, and injunctive), gender (with women being more likely than men to initiate opioid misuse), and educational level with nonmedical prescription opioid use among young adults.

Rice and Klein (2019) conducted a study aimed at examining the interaction between attitudes and perceived norms regarding health-related behaviors among adolescents in the United States. Statistically significant relationships were discovered between adolescents' perceived norms and their own health-promoting and health-impairing behaviors, including unhealthy food consumption, sedentary habits, and fruit and vegetable consumption. My study findings reflect on the significant role which perceived norms may play in both health-impairing and health-promoting behaviors.

Limitations of the Study

Every research study possesses both strengths and limitations. The findings of this study were restricted to young adults who were currently or previously engaged in nonmedical prescription opioid use and were selected as a convenience sample. Therefore, it is possible that these findings may not be applicable to young adults who do not engage in nonmedical prescription opioid use. A convenience sample may result in the underrepresentation or overrepresentation of specific demographic groups in the sample. When a sample is not selected randomly, the convenience sampling method introduces a bias that might result in the sample not accurately representing the population under study (Granello & Wheaton, 2004; Madden, 2016). Most convenience sampling methods frequently produce biased estimates of the target population and its sociodemographic subgroups, resulting in poor generalizability (Jager et al., 2017).

Thus, the findings of my study may not be generalizable to other regions or global continents that do not have multiculturalism or to different geographic areas that have varying demographic characteristics especially if these areas also have distinct micro-cultures and social dynamics within higher institutions that can influence nonmedical prescription opioid use and demographic factors (Dussault & Weyandt, 2013; John, 2021).

Cross-sectional and correlational data were used in the study, so it was not possible to assess causal associations among variables. Self-selection bias of the participants was another possible limitation of this study because only people who are currently taking or have previously used prescription opioids for reasons other than medical purposes completed the online survey. Validity and reliability are crucial factors for approving and validating quantitative research (Madden, 2016). The scales used in this study were found to be reliable based on the results of the Cronbach's alphas.

Data were collected using an anonymous online survey administered via the Qualtrics platform on the internet. Nevertheless, despite my efforts to promote my research through strategically placed the recruitment flyers on and around the campuses, as well as on social media platforms like Facebook and Instagram, I did not observe a significant increase in participation via Qualtrics (an online survey platform) in the first to the second week of data collection. This lack of response can likely be attributed to challenges such as unreliable internet connections, slow internet speeds, and limited access commonly encountered in remote areas where certain Nigerian universities are located (Blanchard, 2021; Ezeonyido, 2016; John, 2021).

Self-administered questionnaires were utilized as data collection instruments in this study. These are based on participant self-reporting, and some of the information provided may have been skewed or inaccurate (see Frankfort-Nachmias et al., 2015; John, 2021). The data provided were based on participant recall of their personal information, which may be difficult to validate because it is widely assumed that recalled information may be biased or distorted if the participant is embarrassed about the behavior being reported (Frankfort-Nachmias et al., 2015). Answering questionnaires necessitates participants to recollect past occurrences, and as the ability to recall and remember diminishes over time, this might result in erroneous reporting (Fadness et al., 2009). To mitigate this concern, researchers employ validated surveys that have consistently showed empirical validity and reliability, despite relying on participants' personal recollections. In addition, I anticipate that the guarantees of anonymity and confidentiality of data have additionally minimized the prospective consequences of this matter (Fadness et al., 2009; Frankfort-Nachmias & Nachmias, 2008; John, 2021).

The statistical power and effect size obtained from the sample size (N = 188) were satisfactory. However, it would be advantageous in further studies to conduct surveys on a larger sample size of university young adults, as this is likely to improve the reliability and generalizability of the results (Faber & Fonseca, 2014). Despite the fact that the data presented in this study differ from those of other comparable investigations, these data offer an alternative viewpoint on the expanding field of research. The current body of research on NMPOU among young adults in Nigeria is limited in scope. Notwithstanding the inherent constraints of this study, the research findings would advance the dialogue surrounding NMPOU among young adults, particularly university and non-university students within the same age range and make a scholarly contribution to the existing dearth of literature. The study's findings are anticipated to provide valuable insights for community leaders, policymakers, university administrators, and policy makers as they endeavor to implement diverse good health behavior strategies and policies pertaining to campus activities and communities.

Recommendations

Future research is undoubtedly required as the opioid epidemic worsens; there is a significant need to be filled in determining the variables that lead to nonmedical prescription opioid misuse and their level of influence on intervention policy and action. For example, by recognizing an association between perceived norms, gender (with women being more likely than men to initiate opioid misuse), educational level, and nonmedical prescription opioid use, local public health organizations can provide better opioid intervention crisis programs or alter policy to ensure a healthier community. My study used participants enrolled in an authorized university to investigate the prevalence rate of nonmedical prescription opioid use among young adults in Nigeria. It may be useful to conduct comparison research among young adults in other sub-Saharan African countries or developed countries with similar micro-cultures to see if their findings agree with or differ from my findings. Furthermore, conducting a comparative analysis of data collected in Nigeria and other countries would yield valuable insights regarding commonalities and distinctions (Dussault & Weyandt, 2013; John, 2021). A comparative study could be conducted by surveying young adults aged 18 to 25 years old who are not enrolled in university or are dropouts. The purpose of this study would be to apply IBM constructs in investigating possible correlation and potential demographic differences with nonmedical prescription opioid use (Denham, 2014; John, 2021).

Several factors in the study were on the verge of reaching statistical significance. Future studies should use a larger sample size to see if a degree of significance can be achieved. Future studies should assess participants' basic knowledge by applying IBM constructs in probing unhealthy behavior within the study and use it as a covariate and/or predictor variable to ensure participants have an accurate understanding of the approach to mitigating the public health concern caused by opioid misuse and addiction among young adults (Madden, 2016). A longitudinal study where data is collected throughout time at different periods may provide greater insight into NMPOU and IBM constructs (John, 2021).

It will be good to broaden the scope of future studies on nonmedical prescription use among young individuals. To obtain a more comprehensive understanding, it is advisable to conduct qualitative research that involves conducting in-depth interviews with young adults. Interviews can uncover information that may not have been obtained from the self-administered questionnaire about attitudes, perceived norms, and personal agency in nonmedical prescription-level opioid use (John, 2021).

Implications

This section presents professional practice guidelines and positive social change implications for nonmedical prescription opioid users in their communities and tertiary institutions. Young adults' substance misuse, particularly the illegal use of prescription opioids, is on the rise in Nigeria, with little regard for the consequences for their health or the greater community (UNODC, 2018). There is an opportunity in our society to give optimal and efficient care to young adults who are involved in opioid misuse and addiction in a timely manner.

Professional Practice

This research is being guided by me to be a good assessment for young adults who use opioids for nonmedical purposes in tertiary institutions, communities, marketplaces, and the level of care options accessible for opioid users. Within this subsection, I am suggesting methodological, theoretical, and empirical applications to professional practice.

Methodological

The data obtained from an anonymous online survey was analyzed using descriptive statistics and a multiple linear regression model. Nevertheless, alternative methodologies could have been employed to ascertain an outcome. My study used a continuous dependent variable to determine the association with the predictor variables. To conduct future research, I recommend employing logistic regression using a categorical dependent variable where the respond to the frequency of opioid use survey requires 'yes or no' answers to analyze large populations of young adults, encompassing both educated and uneducated individuals between 18 to 25 years old. The importance of logistic regression offers more accurate prediction of patterns and probability of association among variables. Secondly, logistic regression can be used to assess internal and external factors influencing nonmedical prescription opioid use among young adults (Noeryanti et al., 2018).

Another method that may be helpful is path analysis. Path analysis is a method used to examine the causal relationship between variables, allowing for the identification of both direct and indirect influences of independent factors on the dependent variable (Noeryanti et al., 2018). Path analysis may have been employed to ascertain the presence of variability necessary for conducting the investigation (Yammine and Rammal, 2021). Path analysis has also been extensively utilized in medical and social science research. Hardenberg and Gonzalez-Voyer (2013) developed a path analysis model utilizing a linear equation system for application in phylogenetic research. Path analysis requires researchers to explicitly define the associations between the dependent variable and two or more independent variables (Yammine & Rammal, 2021). This study used cross-sectional data, which means it was collected at a single point in time rather than pre- and post-events. Cross-sectional data may present challenges when performing time-to-event analysis or survival analysis. Time-to-event analysis is a set of methodologies for examining the duration of time until a well-defined end point of interest occurs (Schober & Velter, 2018). Time-to-event analysis provides researchers with vital information regarding how long it took for a certain change to occur (In & Lee, 2018; Schober & Velter, 2018). Despite the lack of path analysis and time-to-event analysis, a significant association was found between perceived norms, gender, educational level, and nonmedical prescription opioid use among young adults in Nigeria.

Theoretical

Given that young adulthood is a critical phase for the development of health behaviors and there is the need for protecting health, not just during the transitional years but over the life course (Arnett, 2000; Bonnie et al., 2015), Fishbein's IBM is the health behavior model utilized in this study and it was essential in understanding the continual development of young adults' attitudes, perceived norms, and personal agency across life course (Bonnie et al., 2015; Fishman et al., 2021). The knowledge from the study findings will enable the design of customized interventions aimed at preventing opioid misuse and addiction. Fishbein's IBM postulates that the likelihood of performing a behavior could be influenced by the individual's behavioral intention which can be triggered by perceived social pressure to perform the behavior. Fishbein and Yzer (2003) argued that while researchers can create measures of attitudes, perceived norms, and self-efficacy from their offices, they cannot accurately determine the beliefs of a certain demographic or individual regarding a particular behavior (p. 168). Fishbein's IBM does not recognize an individual's risk perception have a direct influence on the person's health behavior. Hence, Fishbein categorizes risk perception as a distal factor with no direct association with the behavior within the IBM (Fishbein, 2002). Future research should employ Affect Heuristic Theory (AHT) in conjunction with IBM and prioritize preliminary research to get insight into the target audience's distinct perspectives, attitudes, and risk perception.

According to Dr. Paul Slovic’s AHT, an individual’s emotions have an impact on both their decision-making process and their perception of risks (Slovic, 2002). Slovic’s affect heuristic is based on the premise that emotional reactions are influenced by two distinct cognitive systems: the analytic system and the experiential system. Slovic’s AHT can be used to investigate the influence of young people’ benefit from NMPOU on their positive affect towards the opioids and their perception of the risks associated with NMPOU (Slovic & Peters, 2006).

Empirical

This research utilized IBM constructs and covariates (such as age, gender, and educational level) to investigate the associations with nonmedical prescription opioid use among young adults. Fishbein’s IBM defines intention as the desire to perform a behavior, which has been demonstrated to predict the likelihood of performing that behavior (Fishbein et al., 2002). IBM can help evaluate an individual’s intention, emotions, self-control, and sociobehavioral perspectives, all of which influence opioid addiction in young adults aged 18 to 25 years old. The empirical implications of the IBM in the study could potentially decrease the prevalence of nonmedical prescription opioid use among young adults by providing behavioral health services to opioid addicts in tertiary institutions and public health centers. This framework presents efficacious behavior modification and intervention strategies aimed at reducing the prevalence of opioid abuse disorders, physical harm, and the financial burdens associated with opioid misuse and addiction among young adults.

Positive Social Change

My research has significant implications for positive social change as it offers researchers and scholars/practitioners the chance to contribute to the current understanding of NMPOU. Specifically, it provides information on the predictive relationships between attitudes, perceived norms, personal agency, and NMPOU, while controlling for age, gender, and educational level. The findings of this study may significantly contribute to the ongoing development and revision of curricula, policies, and programs for tertiary institutions and communities on a regular basis. This modification has the potential to guarantee that young adults between 18 to 25 years old who are vulnerable to certain opioid misuse or risks are provided with information and support that can lead to better health decisions and societal transformation. Additionally, it may help mitigate the negative consequences of stigmatization on the well-being of opioid users especially college students, as well as decrease the risks associated with NMPOU among this population.

This study promotes positive social change by increasing public health awareness campaigns in tertiary institutions and communities which will aid in the decrease of NMPOU and the improvement of desired health behaviors. Furthermore, this research will raise awareness of sociocultural norms, traditions, and practices that place young adults at risk of NMPOU.

Conclusion

The purpose of this study was to examine the predictive relationship between three Integrated Behavior Model constructs (attitudes, perceived norms, and personal agency) and nonmedical prescription opioid use in young adults while controlling for age, gender, and educational level. The theoretical framework of the study was Fishbein's integrated behavior model (IBM). This study employed a cross-sectional methodology to quantitatively analyze primary data collection. Primary data was collected through an anonymous online survey of university students in Nigeria who met the specified inclusion criteria. The online survey data collection instrumentation consists of an implied consent form, demographic form, and IBM questionnaires for primary outcomes and latent constructs.

As hypothesized, attitudes and personal agency do not have significant relationship with NMPOU. Hence, the hypotheses cannot be rejected though the covariates (gender and educational level) show a significant association in the model. Gender was a significant predictor in our model. The study showed that there was a marginally higher likelihood of nonmedical prescription opioid use among females in comparison to males in all hypotheses. In the model, educational level is another significant predictor in the model with nonmedical prescription opioid use among young adults. The descriptive analysis showed that students in the sophomore level showed a higher chance in opioid misuse for nonmedical purposes compared to the other educational levels.

My key findings are however consistent with previous researchers who found perceived norms (descriptive, subjective, and injunctive norms), gender (females have higher chances of initiating NMPOU compared to males) and educational level (post-secondary students are more likely to initiate NMPOU compared to high school students

(Ashrafioun et al., 2017; Bakhshale et al., 2019; Cho et al., 2021; Martinez, 2017; McCabe et al., 2017). Future studies should assess participants' basic knowledge by probing unhealthy behavior within the study using Affect Heuristic Theory (AHT) to investigate individual's risk perception in conjunction with Integrated Behavior Model constructs and covariates such as gender, educational level to ensure participants have an accurate understanding of the approach to mitigating the public health concern caused by opioid misuse and addiction among young adults (Madden, 2016).

This study aims to facilitate positive societal transformation by enhancing public health awareness campaigns, thereby contributing to the reduction of nonmedical prescription opioid use (NMPOU) and the promotion of desired health behaviors. Moreover, this study will enhance understanding of sociocultural norms, traditions, and behaviors that expose young adults to the dangers of nonmedical prescription opioid use.

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Appendix A: Demographic Form

Instructions: please tick or mark the right option that fits your description.

1. Age

18 to 25 years --- [] yes or [] no

2. Gender

Male [] or Female []

3. Education

University undergraduate levels

(a). Freshman (100 level) ---------------------------------- []

(b). Sophomore (200 level) ------------------------------- []

(c). Junior (300 level) ------------------------------------- []

(d). Senior (400 level) ------------------------------------ []

University post-graduate levels

(e). Master's degree level -------------------------------- []

(f). Ph.D. degree level ------------------------------------ []

Appendix B: IBM Questionnaires for Primary Outcome and Latent Constructs

Constructs and coding	Behavioral Questionnaires	Answer Options
(a) Primary outcome: Nonmedical prescription opioid use (NMPOU).	Have you heard of or seen opioids before this study?	[]. Yes []. No
Frequency of opioid use	If you answered 'yes' to have heard or seen opioids, how often do you now engage in nonmedical prescription opioid use NMPOU?	[] Everyday [] Some day [] Once a month [] Not at all [] Quit
Opioid source	Where did you collect or buy the opioids you used?	1. Emergency room 2. Dentist 3. Family physician 4. Pain/trauma doctor 5. Parents/or friends 6. Illegal street vendors 7. Stole or other
Initial age of Opioid use (first timers)	How old were you when you first used opioids?	[]. Younger than 18 years []. Between the age of 18 and 25
Commonly available opioids in Nigeria	Which of these opioids have you used or currently using for nonmedical purposes? Indicate by ticking the box.	[] Fentanyl (duragesic) [] Heroin [] Hydrocodone (vicodin) [] Morphine (Mscontin) [] Oxycodone (oxycontin) [] Oxymorphone (opana) [] Tramadol (ultram)
Suicidal Ideation	Have you really considered hurting yourself?	[] yes [] no
(b) IBM Constructs Attitude subconstructs (I) Experiential (positive affect) Feelslikepills	(i) I engage in nonmedical prescription opioid use because I feel like taking painkiller pills	• Strongly agree • Agree • Neutral • Disagree • Strongly disagree
Feelsbeta	(ii) I engage in nonmedical prescription opioid use because help me cope with depression	• Strongly agree • Agree • Neutral • Disagree • Strongly disagree

Thinksbeta	(iii) I engage in nonmedical prescription opioid use because it makes me think better	• Strongly agree • Agree • Neutral • Disagree • Strongly disagree
Feelslonely	(iv) I engage in nonmedical prescription opioid use due to loneliness feelings	• Strongly agree • Agree • Neutral • Disagree • Strongly disagree
Feelsstrong	(v) I feel more energetic after using a nonmedical prescription	• Strongly agree • Agree • Neutral • Disagree • Strongly disagree
(II) Instrumental Attitude (Perceived Benefit)		
Feelstasty	(i) I have sweet taste-like feelings with nonmedical prescription opioid use	• Strongly agree • Agree • Neutral • Disagree • Strongly disagree
NMPOUSmel	(ii) I believe most nonmedical prescription opioid use smells good	• Strongly agree • Agree • Neutral • Disagree • Strongly disagree
NMPOUHlpQuit	(iii) I engage in nonmedical prescription opioid use because it helps me quit other substance use	• Strongly agree • Agree • Neutral • Disagree • Strongly disagree
NMPOUAlt	(iv) I engage in nonmedical prescription opioid use because it serves as an alternative to other substance use	• Strongly agree • Agree • Neutral • Disagree • Strongly disagree
Feelsociable	(v) I feel more connected to your peer groups, social environment, and education when taking nonmedical prescription opioids	• Strongly agree • Agree • Neutral • Disagree • Strongly disagree

Perceived Norm Constructs		
(I) Injunctive Norm		
NMPOAccpt	(i) I feel it is more acceptable to nonopioid users when taking nonmedical prescription opioids	• Strongly agree • Agree • Neutral • Disagree • Strongly disagree
TpBemater	(ii) I think people's behavior towards nonmedical prescription opioid users does not matter	• Strongly agree • Agree • Neutral • Disagree • Strongly disagree
(II) Subjective norms		
FRpPosOp	(i) I feel that peer groups/relatives have a positive opinion towards nonmedical prescription opioid users	• Strongly agree • Agree • Neutral • Disagree • Strongly disagree
FRnNegOp	(ii) I feel that peer groups/relatives have negative opinions towards nonmedical prescription opioid users	• Strongly agree • Agree • Neutral • Disagree • Strongly disagree
OKFrTak	(iii) I feel okay with peer groups/relatives when taking nonmedical prescription opioids	• Strongly agree • Agree • Neutral • Disagree • Strongly disagree
TkPCLoNMPO	(iv) I think people close to you are involved with nonmedical prescription opioid use	• Strongly agree • Agree • Neutral • Disagree • Strongly disagree
TKiPoDrE	(v) I feel that most people using nonmedical prescription opioids derives more excitement from it	• Strongly agree • Agree • Neutral • Disagree • Strongly disagree
(III) Descriptive Norm		
NMPOCeleb	(i) I feel most celebrities, employers, career professionals, and public figures use nonmedical prescription opioids	• Strongly agree • Agree • Neutral • Disagree • Strongly disagree

PeSpdTime	(ii) I think most people spend more time with nonmedical prescription opioid users	• Strongly agree • Agree • Neutral • Disagree • Strongly disagree
PeAttnsekers	(iii) I think most people on nonmedical prescription opioids are attention seekers	• Strongly agree • Agree • Neutral • Disagree • Strongly disagree
PeOrgdz	(iv) I think most people on nonmedical prescription opioids are organized	• Strongly agree • Agree • Neutral • Disagree • Strongly disagree
YoFeelOrgdz	(v) I feel well-organized after taking nonmedical prescription opioids	• Strongly agree • Agree • Neutral • Disagree • Strongly disagree
Personal Agency Constructs (I) Perceived Behavioral Control		
NMPOAfdable	(i) I engage in nonmedical prescription opioids use because opioids are affordable	• Strongly agree • Agree • Neutral • Disagree • Strongly disagree
TaKOpEvrwy	(ii) I engage in nonmedical prescription opioids anywhere even where it is prohibited	• Strongly agree • Agree • Neutral • Disagree • Strongly disagree
(II) Self-efficacy		
HardStoP	(i) I find it hard not to use nonmedical prescription opioids	• Strongly agree • Agree • Neutral • Disagree • Strongly disagree
HardToObt	(ii) I find it hard not to use nonmedical prescription opioids for the next day, weeks, or months	• Strongly agree • Agree • Neutral • Disagree • Strongly disagree