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Predictors of Medication Alternative Cost-Saving Strategies Among Adults with Type 2-Diabetes

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<u>Walden University</u>

College of Health Sciences and Public Policy

This is to certify that the doctoral dissertation by

Olaseni Solomon Oduwaye

has been found to be complete and satisfactory in all respects,
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the review committee have been made.

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Walden University
2022

Abstract

Predictors of Medication Alternative Cost-Saving Strategies Among Adults with Type 2-

Diabetes

by

Olaseni Solomon Oduwaye

MBA, Jones International University, 2011

MSc, Vrije Universiteit Brussels, 1999

Dissertation Submitted in Partial Fulfillment

of the Requirements for the Degree of

Doctor of Philosophy

Health Services

Walden University

May 2022

Abstract

Adults with type 2 diabetes (T2D) in the United States experience a significant financial burden in managing their condition due to prescription medication, higher out-of-pocket (OOP) costs, number of prescribed medications, and health insurance status to stay compliant with their medications. This study examined the association between the alternative medication cost-saving strategies, including obtaining free samples from doctors or patient assistance programs, splitting pills or changing dosage frequency, purchasing from other countries, purchasing over the internet, and the three independent variables among adults diagnosed with T2D. Reasoned action approach theory helped guide how external factors may influence an alternative medication cost savings strategy. A quantitative, cross-sectional survey design was implemented with the Qualtrics platform and questions from the Consumer Assessment of Healthcare Providers and Systems survey instrument. Self-reported responses from adults diagnosed with T2D were administered and captured online from participants registered with the Amazon Mechanical Turk Crowdsourcing Internet Marketplace (mTurk). A multiple binomial logistic regression analysis predicted that health insurance is associated with increased purchasing of medications over the internet. An increase in the number of prescribed medications and OOP expenses is associated with a reduction in purchasing medications from other countries and an increase in splitting pills or changing dosage frequency. Identifying predictors of alternative prescription cost-saving strategies by adults with T2D may help promote personalized medication assistance for those patients experiencing financial hardships to ensure they remain compliant with their medications.

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Dedication

With the grace of God Almighty, I dedicated this work to my parents. My father and mother, Taiwo and Adebimpe Adebayo Oduwaye are both of blessed memory. They never had the opportunity to have an education, but a suspenseful peasant farmer and kola nut trader who had the insight to encourage me through my early childhood education among my siblings who could not go further in their education due to financial struggle. I had to aim for excellence in my education to obtain scholarships that allowed me to be the first to go to college in my family. Although I am not able to repay you for this encouragement, this work is a way of giving back for all my success in life. You will always be remembered for the inspiration.

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I want to acknowledge my chair, Dr. David Segal, my committee member Dr. Mary Lou Gutierrez, and the university research reviewer Dr. James Rohrer for their guidance and support in taking me through the success of this dissertation. I also want to thank Dr. Mountasser Kadrie and Dr. Robin Carlson for their early guidance on this journey. Without my family and friends, including my children, who have gone through this journey with me, the success of this dissertation would not have been possible, so my sincere gratitude to you all.

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Chapter 1: Introduction to the Study

Introduction

Diabetes disease is a severe epidemic in the United States. As the prevalence of diabetes continues to increase, the individual health burden and financial constraints on society grow (Center for Disease Control and Prevention [CDC], 2018). The CDC projects that 53.1 million people within the United States will have diabetes by 2025. According to the National Health Information Survey (NHIS) report data between 2017 and 2018, among 10.1% of U.S. residents' adults diagnosed with diabetes, 7.2% of those over 65, and 35.7% of younger adults below age 65 without health insurance coverage are not likely to have taken their medication as prescribed due to costs (Cohen & Cha, 2019).

The American Diabetes Association (ADA, 2018) reported that diabetes patients without insurance are 60% less likely to visit the physician's office with a 52% chance to be prescribed any medication. However, an older adult with diabetes tends to take more prescription medications each year (ADA, 2018). The challenge of having no health insurance or inadequate (poor) health insurance for diabetes patients increases the risk of additional health problems (Toulouse & Kodadek, 2016). Prescription medication costs constitute a substantial financial burden among adult diabetic patients who use health services in managing their chronic conditions (Toulouse & Kodadek, 2016). The cost of out-of-pocket (OOP) prescription drugs represents one of the highest healthcare costs for Adult diabetic patients, who are uninsured, underinsured, and low-income, prompting the use of cost-saving strategies such as alternative sources for prescription medications to help these patients reduce their out-of-pocket monthly expenses (CMS, 2019; Cohen & Cha, 2019; Cohen & Villarroel, 2015; Musich et al., 2015).

Medication adherence is associated with patients' access to medical care and improved quality of life (Andrews et al., 2017; Guerard et al., 2018; Nerat et al., 2016; Zullig et al., 2015). However, providing access to the most needed medications at a lower cost may be necessary to improve outcomes and reduce healthcare costs (Toulouse & Kodadek, 2016). Adult type 2 diabetes (T2D) patients are more likely to use alternative cost-saving sources that include obtaining samples from physicians, splitting pills, purchasing medication from another country, and purchasing from the internet to reduce the cost of prescription medication (Cohen & Cha, 2019; Cohen & Villarroel, 2015; Musich et al., 2015). However, there is very little information about the association between participants' use of alternative cost-savings strategy and OOP expenses, the number of prescribed medications, and health insurance status in T2D adults controlling for patient demographics and socioeconomics.

This study examined the patient's self-reported response to the above variables and the association of each specific predictor variable with each type of alternative prescription medication cost-saving strategy that includes obtaining samples from physicians or patients assistance programs, splitting pills or changing the dosage frequency, purchasing medication from another country, and purchasing from the internet among T2D adults controlling for patient socioeconomic and demographics factors. The study uses the reasoned action and planned behavior theory to explain how changes in behavior can influence T2D patients' alternative prescription purchase decisions to use one or more alternative cost-saving strategies. The study findings help promote social change in identifying predictors of alternative prescription cost-saving sources for medication compliance among people with T2D.

Background of the Study

Within the United States, 30.3 million people (9.4% of the U.S. population) have diabetes, and 84.1 million (33.9% of the U.S. population) adults aged 18 years or older have prediabetes (CDC, 2017). Diabetes leads to micro-and macrovascular complications with increased co-morbidities, prescription medication use, and higher healthcare costs (ADA, 2018; CDC, 2017; Choi et al., 2016; Toulouse & Kodadek, 2016). Compliance with these antidiabetic prescription medications is critical to successfully treating and managing long-term complications of diabetes (Brown & McBride, 2015; Kleinsinger, 2018). Prescription medications are one of the highest healthcare costs, and patients with diagnosed diabetes experience the most OOP expenses (Cohen & Cha, 2019). However, for adult diabetic patients who use healthcare services, prescription medication costs constituted a substantial financial burden, notably among the uninsured, under-insured, or lower-income (those below 400% of poverty level) adults with diabetes population (Brown & McBride, 2015; Cohen & Cha, 2019; Shepherd et al., 2014; Toulouse & Kodadek, 2016), which is associated with patient's poorer health outcome (Kang et al., 2018).

Thus, to reduce drug cost, most adult diabetic patients who are uninsured, underinsured, or low-income use cost-savings strategies that include obtaining samples from physicians or patient assistance programs, splitting pills or changing the dosage frequency, purchasing medication from another country, and purchasing from the internet (Cohen & Cha, 2019; Cohen & Villarroel, 2015; Musich et al., 2015; Pallarito, 2018). The American Diabetes Association (2018) reported that, on average, adults with diabetes take at least one or more prescribed medication. Over 65 years and above are those covered by Medicare supplement Part D resulting in enormous OOP expenses (ADA, 2018; Cohen & Cha, 2019). Adults' additional options to reduce OOP expenses were reported to include buying directly from the source, using pharmacy store discount cards, or frequently checking the mobile apps for discounts (Pallarito, 2018) or the untrackable claim sources that include purchasing medication from other countries or the internet (Musich et al., 2015). For instance, in one study of consumer behavior to buy medicine online, many consumers that purchased the prescription drug online reported doing so for different reasons (Kennedy & Wilson, 2017).

When considering the need to use alternative medication cost-saving in healthcare services, the strategies can improve access to low-cost prescription drugs that impact patients' outcomes (Musich et al., 2015; Pallarito, 2018). Other researchers have argued that alternative therapy on prescription medication cost-reduction strategies and poorer health status will be impacted by patient non-compliance to the recommended medication regimen (Choi et al., 2016; Cohen & Villarroel., 2015; Kang et al., 2018; Kleinsinger, 2018). Few published studies include diabetes participants on prescription medication cost-saving strategies using various socioeconomic and demographic characteristics (Cohen & Cha, 2019; Musich et al., 2015). However, none of the studies addressed whether OOP expenses, number of prescribed medications, and health insurance status predict the use of cost-savings strategy among adults with T2D. This study focuses on this gap. It explores how the association of the specific variables may identify with each type of prescription medication cost-saving strategies, which included obtaining samples from physicians or patient assistance programs, split pills or changing dosage frequency, purchasing medication from another country, and purchasing from the internet, among T2D adults controlling for patient demographics.

Problem Statement

As the diabetes epidemic's prevalence increases, prescription medications' OOP expenses represent one of the United States' highest healthcare costs. Patients diagnosed with T2D typically take two or more medications monthly. However, T2D patients in the United States with no health insurance, who are indigent, underinsured, or low-income, mostly used prescription medication, which may constitute a financial burden and remain compliant with medication regimens.

In 2017, outpatients' medication expenses for U.S. adults diagnosed with diabetes were approximately $5,000 annual per capita (ADA, 2018; Cohen & Cha., 2019). CMS (2017) survey revealed that in 2017, adults below age 65 spent an average of $8,045 of total annual healthcare services on prescription drugs. The American Diabetes Association (ADA, 2018) reported that people with diabetes are 52% less likely to be prescribed any medication and 62% less likely to visit physicians without health insurance coverage. While patients diagnosed with T2D diabetes tend to take one or more prescription medications, medication expenses constitute a substantial financial burden in managing their chronic conditions (ADA, 2018; Toulouse & Kodadek, 2016).

Researchers in other studies have concluded that using alternative sources for prescription drugs is beneficial to managing drug cost-related access issues, such as lack of insurance, being indigent or underinsured, or being low-income (Choi et al., 2016; Kang et al., 2018; Kleinsinger, 2018). Some studies addressed prescription drug cost-saving strategies and associated medication adherence (Cohen & Villarroel., 2015; Musich et al., 2015). Yet very few studies include diabetes participants' use of prescription medication cost-saving strategies with various demographic characteristics (Cohen & Cha., 2019). However, the studies concluded that adults who are more likely to use the cost-saving strategies have more comorbid conditions, have more disabilities, and use more medications (Cohen & Villarroel, 2015; Musich et al., 2015). Studies that include diabetes participants suggested that cost-saving strategies may be associated with medication nonadherence (non-compliance; Cohen & Cha, 2019; Musich et al., 2015).

Nevertheless, none of the studies addressed whether OOP expenses, number of prescribed medications, and health insurance status predict the use of alternative medication cost-savings strategies among adults with T2D. In this study, I addressed this gap by examining how the association of the specific variables may identify with each type of prescription medication cost-saving strategy, which includes obtaining free samples from doctors or patient assistance programs, split pills or changed dosage frequency, purchasing medication from another country, and purchasing from the internet among T2D adults, controlling for patient socioeconomic and demographic factors.

Purpose of the Study

The purpose of this quantitative, cross-sectional survey design study is to investigate the association between patients' self-reported OOP expenses, the number of prescribed medication, insurance status, and use of each alternative medication cost-saving strategies that includes obtaining samples from physicians or patient assistance programs; split pills or changed dosage frequency; purchases medication from another country; and purchase from the internet in T2D adults controlling for patient socioeconomic and demographic factors. The study used a multiple binomial logistic regression statistical model to analyze the relationship between measurable independent variables relevant to the study objective. The participant's self-reported monthly OOP expenses, the monthly number of prescribed medication, and health insurance status are independent variables of interest that influence participants' usage of each alternative medication cost-saving strategy (dependent variables). The study's dependent variables include obtaining free samples from physicians or patient assistance programs, purchasing medication from the internet, purchasing from other countries, and splitting pills or changing dosage frequency. The covariates (mediating variables) also captured in the CAHPS survey (2018) are determined by individual characteristics such as demographic (e.g., race, gender), socioeconomic status (income, education), health status, and perception of experience and satisfaction with the prescription medication component of healthcare service, which may influence the outcome.

Research Questions and Hypothesis

RQ1a: What is the association between the monthly OOP expenses and purchase of medication over the internet in T2D adults while controlling for patient socioeconomic and demographics?

H_o1a: There is no association between the monthly OOP expenses and purchase of medication over the internet in T2D adults while controlling for patient socioeconomic and demographics.

$H_1$1a: There is an association between the monthly OOP expenses and purchase of medication over the internet in T2D adults while controlling for socioeconomic and demographics.

RQ1b: What is the association between the monthly OOP expenses and purchase of medication from other countries in T2D adults while controlling for patient socioeconomic and demographics?

H_o1b: There is no association between the monthly OOP expenses and purchase of medication from other countries in T2D adults while controlling for patient socioeconomic and demographics.

$H_1$1b: There is an association between the monthly OOP expenses and purchase of medication from other countries in T2D adults while controlling for patient socioeconomic and demographics.

RQ1c: What is the association between the monthly OOP expenses and obtaining free samples from doctors or patient assistance programs in T2D adults while controlling for patient socioeconomic and demographics?

H_o1c: There is no association between the monthly OOP expenses and obtaining free samples from doctors or patient assistance programs in T2D adults while controlling for patient socioeconomic and demographics.

H_11c: There is an association between the monthly OOP expenses and obtaining free samples from doctors or patient assistance programs in T2D adults while controlling for patient socioeconomic and demographics.

RQ1d: What is the association between the monthly OOP expenses and splitting pills or change dosage frequency in T2D adults while controlling for patient socioeconomic and demographics?

H_o1d: There is no association between the monthly OOP expenses and splitting pills or changing dosage frequency in T2D adults while controlling for patient socioeconomic and demographics.

H_11d: There is an association between the monthly OOP expenses and splitting pills or changing dosage frequency in T2D adults while controlling for patient socioeconomic and demographics.

RQ2a: What is the association between the monthly number of prescribed medications and purchase of medication over the internet in T2D adults while controlling for patient socioeconomic and demographics?

H_o2a: There is no association between the monthly number of prescribed medications and purchase of medication over the internet in T2D adults while controlling for patient socioeconomic and demographics.

H$_1$2a: There is an association between the monthly number of prescribed medications and purchase of medication over the internet in T2D adults while controlling for patient socioeconomic and demographics.

RQ2b: What is the association between the monthly number of prescribed medications expenses and purchase of medication from other countries in T2D adults while controlling for patient socioeconomic and demographics?

H$_o$2b: There is no association between the monthly number of prescribed medications and purchase of medication from other countries in T2D adults while controlling for patient socioeconomic and demographics.

H$_1$2b: There is an association between the monthly number of prescribed medications and purchase of medication from other countries in T2D adults while controlling for patient socioeconomic and demographics.

RQ2c: What is the association between the monthly number of prescribed medications and obtaining free samples from doctors or patient assistance programs in T2D adults while controlling for patient socioeconomic and demographics?

H$_o$2c: There is no association between the monthly number of prescribed medications and obtaining free samples from doctors or patient assistance programs in T2D adults while controlling for patient socioeconomic and demographics.

H$_1$2c: There is an association between the monthly number of prescribed medications and obtaining free samples from doctors or patient assistance programs in T2D adults while controlling for patient socioeconomic and demographics.

RQ2d: What is the association between the monthly number of prescribed medications and splitting pills or changing dosage frequency in T2D adults while controlling for patient socioeconomic and demographics?

H_o2d: There is no association between the monthly number of prescribed medications and splitting pills or changing dosage frequency in T2D adults while controlling for patient socioeconomic and demographics.

H_l2d: There is an association between the monthly number of prescribed medications and splitting pills or changing dosage frequency in T2D adults while controlling for patient socioeconomic and demographics.

RQ3a: What is the association between the health insurance status and purchase of medication over the internet in T2D adults while controlling for patient socioeconomic and demographics?

H_o3a: There is no association between the health insurance status and purchase of medication over the internet in T2D adults while controlling for socioeconomic and demographics.

H_l3a: There is an association between the health insurance status and purchase of medication over the internet in T2D adults while controlling for socioeconomic and demographics.

RQ3b: What is the association between the health insurance status and purchase of medication from other countries in T2D adults while controlling for patient socioeconomic and demographics?

H_o3b: There is no association between the health insurance status and purchase of medication from other countries in T2D adults while controlling for patient socioeconomic and demographics.

H_l3b: There is an association between the health insurance status and purchase of medication from other countries in T2D adults while controlling for patient socioeconomic and demographics.

RQ3c: What is the association between the health insurance status expenses and obtaining free samples from doctors or patient assistance programs in T2D adults while controlling for patient socioeconomic and demographics?

H_o3c: There is no association between the health insurance status and obtaining free samples from doctors or patient assistance programs in T2D adults while controlling for patient socioeconomic and demographics.

H_l3c: There is an association between the health insurance status and obtaining free samples from doctors or patient assistance programs in T2D adults while controlling for socioeconomic and demographics.

RQ3d: What is the association between the health insurance status and splitting pills or changing the dosage frequency in T2D adults while controlling for patient socioeconomic and demographics?

H$_o$3d: There is no association between the health insurance status and splitting pills or changing the dosage frequency in T2D adults while controlling for patient socioeconomic and demographics.

H$_l$3d: There is an association between the health insurance status and splitting pills or changing the dosage frequency in T2D adults while controlling for patient socioeconomic and demographics.

RQ4a: What is the association between the insurance status, monthly OOP expenses, monthly number of prescribed medications, and purchase of medication over the internet in T2D) adults while controlling for patient socioeconomic and demographics?

H$_l$4a: There is an association between the insurance status, monthly OOP expenses, monthly number of prescribed medications, and purchase of medication over the internet in T2D adults while controlling for patient socioeconomic and demographics.

H$_o$4a: There is no association between the insurance status, monthly OOP expenses, monthly number of prescribed medications, and purchase of medication over the internet in T2D adults while controlling for patient socioeconomic and demographics.

RQ4b: What is the association between the insurance status, monthly OOP expenses, monthly number of prescribed medications, and purchase of medication from other countries in T2D adults while controlling for patient socioeconomic and demographics?

$H_1$4b: There is an association between the insurance status, monthly OOP expenses, monthly number of prescribed medications, and purchase of medication from other countries in T2D adults while controlling for patient socioeconomic and demographics.

H_o4b: There is no association between the insurance status, monthly OOP expenses, monthly number of prescribed medications, and purchase of medication from other countries in T2D adults while controlling for patient socioeconomic and demographics.

RQ4c: What is the association between the insurance status, monthly OOP expenses, monthly number of prescribed medications, and obtaining free samples from doctors or patient assistance programs in T2D adults while controlling for patient socioeconomic and demographics?

$H_1$4c: There is an association between the insurance status, monthly OOP expenses, monthly number of prescribed medications, and obtaining free samples from doctors or patient assistance programs in T2D adults while controlling for patient socioeconomic and demographics.

H_o4c: There is no association between the insurance status, monthly OOP expenses, monthly number of prescribed medications, and obtaining free samples from doctors or patient assistance programs in T2D adults while controlling for patient socioeconomic and demographics.

RQ4d: What is the association between the insurance status, monthly OOP expenses, the monthly number of prescribed medications, and splitting pills or changing the dosage frequency in T2D adults controlling for patient socioeconomic and demographics?

H_l4d: There is an association between the insurance status, monthly OOP expenses, the monthly number of prescribed medications, and splitting pills or changing the dosage frequency in T2D adults while controlling for patient socioeconomic and demographics.

H_o4d: There is no association between the insurance status, monthly OOP expenses, the monthly number of prescribed medications, and splitting pills or changing the dosage frequency in T2D adults controlling for patient socioeconomic and demographics.

Independent Variables (IV)

The measured participant's monthly OOP expenses, the monthly number of prescribed medications, and health insurance status (captured using adapted CAHPS, 2018) are independent variables.

Covariates Variables (CV)

Captured in the CAHPS, 2018, factors that may influence the outcome, such as demographics (age, race, gender) and socioeconomic status (income, education), are covariables in this study.

Dependent Variables (DV)

Respondents used alternative cost-saving strategies that included obtaining free samples from physicians or patient assistance programs, medication purchases from the internet, medication purchases from other countries, and splitting pills or changing dosage frequency, which are four separately measured dependent variables in the study.

This study used a cross-sectional self-reported survey (Appendix 1). The survey questionnaire was captured in the adapted publicly available CAHPS survey (2018) and designed in the Qualtrics platform, distributed online through the Amazon Mechanical Turk Crowdsourcing Internet Marketplace. The two-part survey includes seven questions. Part 1 measured respondents' responses to demographics and socioeconomic characteristics.

Part 2 collected information on respondents' self-reported responses to the questions that measure relevant variables in this study: health insurance status, monthly OOP expenses, and the number of prescription medications (IV). Alternative cost-saving strategies are defined to include the following (DV): taken samples from physicians or patient assistance programs, purchasing medication from the internet, purchasing medication from other countries, splitting pills, or changing dosage frequency.

Theoretical Foundation

This study's theoretical foundation was the reasoned action approach, which incorporates Ajzen and Fishbein's (1980, 1985, 1991) theory of reasoned action (TRA) and the theory of planned behavior (TPB). TRA's premise is that attitudes based on beliefs are cognitions that link attributes and behavior (Hale et al., 2002). According to TRA, a person's attitude and subjective norm influence the person's degree of intent to engage in a specific behavior, subsequently predicting acceptance of such action (or practice; Ajzen and Fishbein, 1980). Fishbein and Ajzen (1975) expressed the strength of a person’s behavioral intention (BI) using the following formula: BI. = A + SN, where A represents evaluative effect (i.e., positive or negative), or the attitude or feelings of the individual toward a target behavior, and SN refers to the subjective norm or the perceived social pressure (positive or negative) concerning the target behavior. Ajzen and Fishbein (1980), the originators of TRA, contended that the theory was “designed to explain virtually any human behavior” (p. 4).

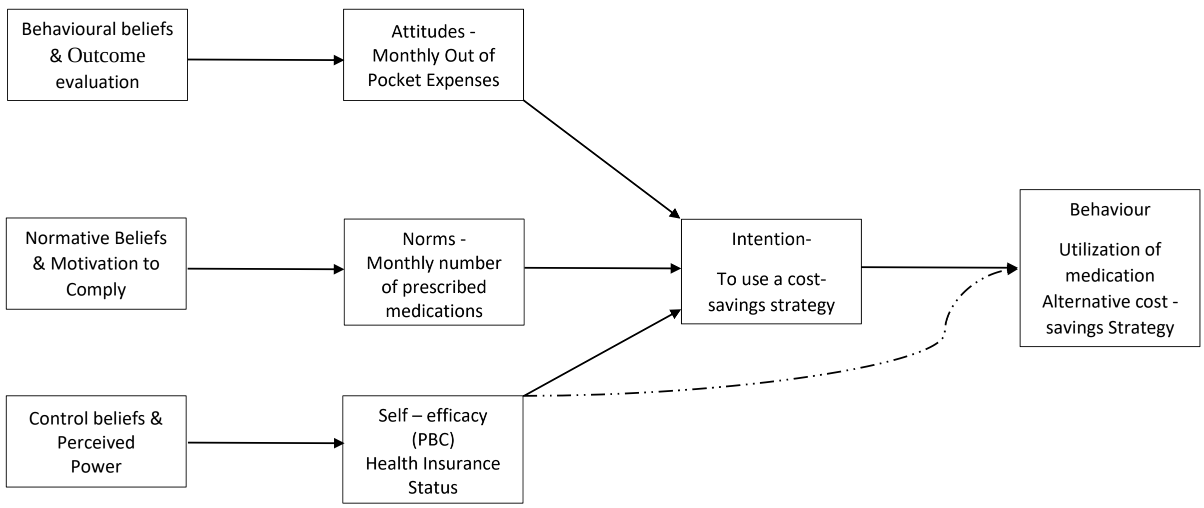
For greater applicability of the TRA to the explanation and prediction of behaviors in situations of incomplete control, Ajzen (1985, 1991) added actual or perceived behavioral control (PBC) to the TRA model and renamed the model the TPB (La Barbera & Ajzen, 2020). Subsequently, Fishbein and Ajzen (2010) developed the reasoned action approach model. They interpreted PBC as how individuals believe that personal and environmental factors hinder or advance their efforts to perform a behavior (Jian et al., 2016). Within the TPB and reasoned action approach model, PBC is expected to moderate the effects of attitude (ATT) and subjective norm (SN) in actual BI (La Barbera & Ajzen, 2020). For example, when ATT and SN are favorable, it is believed that the intention to perform a behavior is favorable (i.e., the extent of the person’s perceived control over the behavior is high; La Barbera & Ajzen, 2020). In other words, together, ATT and SN, moderated by PBC, shape an individual’s BI and behavior (Karimy et al., 2019; La Barbera & Ajzen, 2020).

Previous studies have established that people who use cost-saving strategies such as purchasing medication online or asking their physicians for lower-cost medication have positive attitudes toward such behavior, largely for cost reasons (Cohen & Cha, 2019; Kennedy & Wilson, 2017). In this study, participants may be driven toward using or intending to use cost-saving strategies by individual attitudinal concern and perception of the prescription load to save money on their prescribed medications (Fishbein, 2008). Other studies have revealed the applicability of the PBC construct and planned behavior or reasoned action approach in predicting intentions (Jian et al., 2016; Karimy et al., 2019; La Barbera & Ajzen, 2020). For example, a study conducted to determine the risk factors associated with self-medication indicated that demographic variables (e.g., age, gender, educational level) and patients' health insurance status were significant predictors in patients' use of self-medication (Karimy et al., 2019). Additionally, Jian et al.'s (2016) study on predictors of return-to-work intention among unemployed adults with multiple sclerosis (MS) revealed that demographics, ATT, SN, and PBC are likely predictors of return-to-work intention.

The above studies informed the reasoned action approach to explaining predictors of intention (or behavior change) using alternative medication cost-saving strategies among T2D patients while controlling for sociodemographic factors. According to Fishbein (2008), individual "behavioral beliefs (often referred to as cost-benefits or outcome expectancies), normative beliefs, and control beliefs" are important variables when considering predictors or changes in each behavior (p. 835). Thus, the reasoned action approach model combines TRA and TPB, including the major variables, intention, attitude, perceived norms, self-efficacy, or PBC (see Figure 1).

Figure 1

Reasoned Action Approach Model



Note. Adapted from "A Reasoned Action Approach to Health Promotion," by M. Fishbein, 2008, *Medical Decision Making, 28*, p. 838 (https://doi.org/10.1177/0272989X08326092). Copyright 2008 by SAGE publication Adapted with permission (Appendix B).

Using a multiple binomial logistic regression statistical model analysis, I examined three independent variables of interest: respondent self-reported monthly OOP expenses (measure participants' attitudinal concern towards using and intention to use cost-saving strategies to save money on their prescription medication); the subjective norm, monthly numbers of prescribed medication (variable used to estimate individual participants believe or perceived social pressure to perform or not perform the behavior needed to comply with their medication regimen), and; the PBC is the participant's self-reported insurance status that moderates the effects of ATT and SN in actual BI (Fishbein, 2008; Fishbein & Ajzen, 2010; La Barbera & Ajzen, 2020). The three independent variables predicted individual beliefs or intention to use each cost-saving strategy (dependent variable) while controlling for socioeconomic and demographic background factors, influencing BI (Fishbein, 2008).

The study variables were operationalized using a modified CAHPS survey instrument. The self-reported CAHPS survey questionnaire measures participant demographics, socioeconomic factors, health status, and perception of experience and satisfaction with different healthcare service components. Applying this concept in healthcare service and behavioral practice answered the study's research questions to examine the association between OOP expenses, the number of prescribed medications, insurance status, and the use of each cost-saving strategy that includes obtaining samples from physicians or patient assistance programs, splitting pills or changing dosage frequency, purchasing medication from another country, and purchasing medication from the internet in T2D adults controlling for patient socioeconomic and demographics factors.

Nature of Study

This quantitative study was a cross-sectional self-reported survey designed and descriptive study derived from primary data. The study design was selected to examine participants who are more likely to use alternative medication cost-savings strategies due to financial burdens, including monthly OOP expenses, the monthly number of prescribed medications, and insurance status (IV). The study used a multiple binomial logistic regression statistical model to determine whether the independent variables predicted the patient's use of cost-savings strategies to reduce prescription medication costs among adults with T2D. The study also controls for participants' characteristics, including socioeconomics (e.g., income, education) and demographics (such as gender, race, age), that could influence the observed relationship among the variables. The result may facilitate a discussion to change policies on the validity of the source of alternative prescription medication cost-saving strategies to reduce the cost of healthcare and medication compliance.

The cost-saving strategies (DVs) included in this study, data collection, and reporting consist of four dependent variables measured separately. They include taking free samples from doctors or patient assistance programs, purchasing medication from the internet, purchasing medicines from other countries, splitting pills, or changing dosage frequency to make medication last longer. However, using this alternative cost-savings strategy is associated with medication nonadherence (Musich et al., 2015). The administrative pharmacy database cannot accurately document the cost-savings strategy variables examined in this study because such sources are not traceable in CMS claims (untrackable source; Musich et al., 2015). Other sources, such as purchasing medication directly from the source or retail outlet, obtaining a discount card or another source of insurance coverage, using the generic drug, and mail order was not included in this study variables because they were often tracked in the administrative pharmacy database and included in CMS claims (Musich et al., 2015). The predictors (IVs) compared in this study, including the respondent's monthly OOP expenses, the monthly number of prescribed medications, and insurance status, are not evaluated in other studies, which is unique to this study design. The CVs include demographics, socioeconomic factors, or characteristics influencing the study outcome.

This cross-sectional design study used the participant's self-reported survey questionnaire response captured in the validated CAHPS survey instrument (2018) Question 1-7 and modified Question 8-12 reported by Musich et al. (2015) and Question 13 reported by Jian et al. (2016), respectively (Q 8-13, publicly available). The self-reported survey was designed on the Qualtrics platform and distributed online through Amazon Mechanical Turk Crowdsourcing Marketplace (mTurk). The survey was restricted to U.S. residents and adults diagnosed with T2D aged 18 years or older who used a prescription medication in the last 12 months. This distribution technique enabled me to maximize the target population (Adepoju et al., 2019). The two-part survey questions include patients' self-reported responses to a four-item checklist (Questions 12 and 13), which measured participants' self-reported intention to use each alternative cost-savings strategy. The participant's self-reported response to five scale items that measured monthly OOP expenses and the monthly number of prescribed medications and insurance status (IV) for this study's objective was also included in the two-part survey. Survey Part 1 included participant's self-reported response to socioeconomic (e.g., income, education) and demographic (such as gender, race, and age) factors (CV).

The IBM SPSS version 27.0 was used to conduct statistical analysis. Multiple binomial logistics regression models were used to test the study's variables' statistical significance. The Cronbach's alpha procedure on SPSS statistics was used to measure the survey response bias's for internal consistency (reliability) in a questionnaire that measures a set of variables in a scale. However, one construct in the study used a self-designed self-reported question, reflecting different underlying factors that employed the questionnaire (Survey Q13). The utility of this approach to assess survey selection bias and reliability was reported in Jian et al. (2016) and Karimy et al. (2019).

Definitions

Cost-saving strategies (operationalization): defined in this study as the use of any of the following untraceable in CMS claim sources to obtain prescribed medication: taken samples from physicians or patients assistance programs; purchasing medication from the internet; buying medication from other countries; and splitting pills or changing dosage frequency (Cohen & Villarroel, 2015: Musich et al., 2015; Pallarito, 2018).

Demographic factors: In this study is participants' responses to individual characteristics that include age (measured in years), gender (two categories: male and female), and race-ethnicity (three categories: White, Black or African American, and Latino ethnic background; Jian et al., 2016).

Health insurance status: In this study referred to as cost-related access barrier (CRAB), a barrier to access prescription medication due to financial stress that includes:

Uninsured: lack of insurance is a barrier to obtaining prescription medicines among adults with chronic illness (Baicker et al., 2017).

Underinsured: older adults eligible for Medicare or Medicare supplement insured patients or insured adults who paid OOP copayments to access prescription medication (Musich et al., 2015).

Health service use (healthcare service): Defined in this study as the service patient's encounter in the use of pharmaceutical and medical services (Shepherd et al., 2014; Toulouse & Kodadek, 2016)

Low-income: individuals with income at or below 400% of the federal poverty line. Thus, the eligibility income level for Medicaid and Affordable Care Act (ACA) insurance coverage (Baicker et al., 2017; Miller et al., 2015).

A monthly number of prescription medications: In this study, participants' responses to the number of prescribed medications taken for their diabetes condition in a month (ADA, 2018).

Monthly out-of-pocket (OOP) expenses: In this study, participants' responses to prescription drug monthly OOP expenses, including Medicare supplement insured patients, resulted in OOP copayments (Musich et al., 2015).

Prescription medication: a prescribed drug with instructions on usage by physicians or health care practitioners (CMS, 2017).

Socioeconomic factors: In this study is participants' responses to individual characteristics to income (measured in U.S. dollars) and education (measured on a scale ratio 1 to 5; CAHPS, 2018).

Untraceable claim: an alternative source of prescription medication (cost-saving strategy) when the source cannot be tracked on the pharmacy manager's or CMS claim record (Musich et al., 2015).

Assumptions

The study was based on the patient's self-reported response to survey questions and my assumption that participants would understand the instructions. Thus, I assumed that the respondents answered the questions to the best of their understanding. However, because the study was a cross-sectional self-reported survey design, I assumed that the statistics and statistical computer program for testing the hypothesis that relates variables drawn from the sample to the study population were appropriate (Creswell, 2014). Therefore, multiple binomial logistic regression statistical tests were used to answer the research questions related to three independent variables of interest and each continuous dependent variable that yielded the study's expected relationship.

Scope and Delimitation

The study was based on the participants' self-reported responses to survey questions that measured the research-specific variables of interest, the categorical variables (health insurance status), or on a scale item measured in ordinal but ranked as continuous variables (monthly OOP expenses and monthly numbers of prescribed medication). I assumed that participants would understand the instructions and respond to the study objectives in a questionnaire, measuring participants' financial burden to comply with the medication regimen among adults diagnosed with T2D. While the study controls demographic and socioeconomic factors, previous studies signified that those factors influenced the expected outcome (Cha & Cohen, 2019; Musich et al., 2015). Using binomial multiple regression statistical tests to answer the research questions and using the Cronbach alpha procedure to measure internal consistency (survey response reliability) on a set of variables in a scale that employed the questionnaire may accurately predict the likelihood of three independent variables of interest and utilization of each continuous dependent variable of interest. However, the survey respondents may not represent the entire uninsured, underinsured (Medicare insured OOP expenses), or low-income (below 400% poverty level) adult T2D patients that used prescribed medication in the United States. At the same time, the study did not evaluate the traceable claim source or alternative cost-savings strategy and the expected outcome. The behavioral determinant assessment based on the reasoned action and planned behavior theory PBC construct may not perfectly describe all the predictors associated with using alternative cost-savings strategies in this study (Karimy et al., 2019; Jian et al., 2016).

Limitation

The study sample only included adults diagnosed with T2D who used prescription medication. However, it may oversample those with or without insurance, which may affect the generalizability of the population. Also, Chandler and Shapiro (2016) reported that while the actual population is unknown, the active member of the mTurk population is likely to be close to 15,000. The nonprobability nature of the mTurk population sample used in this study may be of concern because it might not completely represent the actual T2D population in the United States, affecting the study’s generalizability (Chandler & Shapiro, 2016). In addition, the sample size is small. Besides, respondents may be at risk of survey fatigue because of other tasks that earn more money. This observation suggests that a short period is given for participants to respond. The nature of the survey administration (Amazon Turk) may have brought some pressure on the sample population to answer without giving much thought to the survey questions, especially the self-reporting of participants' response to the variables objective to this study, which is likely to affect the external validity (Adepoju et al., 2019). Thus, I used the Cronbach procedure to test the reliability of the survey questionnaire response to measure the internal consistency of a set of variables in a scale, i.e., the four separate dependent variables measured in this study (participants' "intention" to use cost-saving strategy for study theoretical perspective). Since one construct in the study used a self-designed self-reported question, reflecting different underlying factors that employed the questionnaire (Survey Q13). I conducted a Cronbach's alpha procedure on SPSS statistics to measure internal consistency (reliability) on the questionnaire employed to measure the constructs on samples to determine or adjust for survey response selection bias (Jian et al., 2016; Karimy et al., 2019).

Significance

The study is critical because T2D patients need improved access to affordable medication. Therefore, prescription medication cost-savings decision strategies may be useful for many patients to access affordable, consistent drugs to manage medication compliance for health services use. Also, since adult T2D patients tend to be on many medications and a significant portion of Medicare is OOP, this study will add to the existing knowledge and advance policy initiatives. Understanding the prevalence and legitimacy of predictors and alternative prescription medication cost-saving strategies, mostly untrackable claim sources, may help reduce healthcare costs and improve affordability and compliance. Thus, the primary purpose of this study was to investigate the association (if any) between patients' self-reported OOP expenses, the number of prescribed medication, insurance status, and use of each cost-savings strategy that includes obtaining samples from physicians, splitting pills, purchasing medication from another country, and purchasing from the internet by T2D adults controlling for patient demographics.

Significance to Theory

The reasoned action and planned behavior theory that guided this study will explain better the extent of how the attitude towards behavior and subjective norm moderated by PBC influence an individual BI or change behavior to use each alternative medication cost-savings strategy (Jian et al., 2016; Karimy et al., 2019; La Barbera & Ajzen, 2020). Thus, the theory prediction will descriptively help explain the study results and how patients' self-reported monthly OOP expenses, monthly numbers of prescribed medication, and insurance status influence the use of specific untrackable claim source cost-savings strategies to reduce the cost of prescription medication. For example, health insurance status is believed to link with health behavior and intention to self-medicate among women (Karimy et al., 2019). Reasoned action approach prediction to explain the association between these variables will contribute to the existing theory in health service and behavioral practices.

Potential Contribution to Advance Knowledge in Health Services

This research study addressed a gap in the literature. The study examined whether the monthly OOP expenses, the monthly number of prescribed medications, and patients' insurance status are potential predictors in using alternative medication cost-savings strategies among T2D adults to reduce prescription drug financial burden. Thus, the study is relevant in health services because the low-income, uninsured, and underinsured adult T2D population needs to improve access to affordable medication and lower prescription medication to reduce OOP spending. Therefore, the study expands understanding of the association between variables considered, guiding the effort to add to existing health services literature.

Potential to Advance Policy and Practice

The study contributes to advance policy and practice by identifying the predictors of use of certain alternative medication cost-savings strategies that may help reduce higher healthcare costs for T2D patients. Medication cost-related access, including patient's insurance status to prescription medication among the adult T2D patients that use health services, require different approaches. However, using a cost-savings strategy may be a source to access affordable, consistent medicines to treat their acute and chronic illnesses (Cohen & Cha, 2019; Musich et al., 2015). The study findings provide health services practitioners and policymakers opportunities to understand significant reasons for using alternative medication cost-savings strategies that benefit healthcare consumers' access to afford all prescribed medication and mitigate the risk of medication non-compliance among adult T2D patients.

Potential Social Change Implication

The knowledge gained and practice implication in identifying predictors of using alternative medication cost-saving strategies to reduce higher healthcare costs and access medication among T2D patients is a positive social change. The study result may help explain the social change implication of the importance of financial burden that OOP expenses, number of medications, and type of health insurance may have on T2D patients in compliance with their prescribed medication regimen. Thus, the study contributed to understanding of how a lack of insurance, being underinsured, having OOP expenses, and having multiple prescribed medications influence the use of alternative prescription medication sources that impact compliance in the T2D adult population. The study findings also positively implicate social change, validating potential alternative sources for prescription medication that are not traceable in pharmacy manager or CMS claims but to reduce healthcare costs among T2D patients.

Summary and Transition

This quantitative study was a cross-sectional survey design derived from primary data. The survey was captured in a modified CAHPS, 2018, designed in the Qualtrics platform, and administered online through the Amazon Mechanical Turk crowdsourcing marketplace. Understanding how OOP expenses, the number of prescribed medications, and insurance status prompted the use of cost-saving strategies to source low-cost prescription medication is significant. Therefore, this study included adults diagnosed with T2D who are 18 years old or older, more likely to use more medications, who have comorbid conditions or disabilities. The study determined whether using an untrackable alternative source of drugs to reduce prescription medication costs is associated with OOP expenses, the number of prescribed medications, and insurance status in T2D, controlling for patients' socioeconomic and demographic factors.

Financial consideration or cost-related access barriers may influence older adults with diabetes or other chronic ill disease conditions to use an alternative source of prescription medication known as medication cost-saving strategies (Cohen & Villarroel, 2015; Musich et al., 2015). Researchers have also associated using these strategies to access the low-cost prescription drug with medication adherence in the Medicare supplement population (Musich et al., 2015). Researchers in other studies have concluded that the use of alternative sources of prescription drugs are beneficial to managing drug cost-related access issues, such as lack of insurance or being indigent, underinsured, or low-income (Choi et al., 2016; Cohen & Cha, 2019; Cohen & Villarroel, 2015; Kang et al.,2018; Kleinsinger, 2018; John et al., 2014; Musich et al., 2015; Zhang & Balk, 2014). Few studies include diabetes participants' prescription medication cost-saving strategies (alternative sources of a prescription drug) with various demographic characteristics (Cohen & Cha, 2019; Musich et al., 2015). However, there is very little information on whether there is an association between the monthly OOP expenses, number of prescribed medications, insurance status (IV), and the use of each cost-savings strategy (DV) that includes obtaining samples from physicians, splitting pills, purchasing medication from another country, and purchasing from the internet in T2D adults controlling for patient socioeconomic and demographics.

The results of this study help explain the social change implication of the importance of financial burden that OOP expenses, number of medications, and type of health insurance may have on T2D patients in compliance with their prescribed medication regimen. The findings thus expand knowledge and understanding of the factors that commonly influence the use of cost-savings strategy to access and save costs on prescription medication, thereby guiding the policy effort to address prescription medication financial burden and improve access to prescribed medication among the T2D patients' population.

The next chapter provides a literature review that establishes the problem's relevance and highlights the literature gap. It describes the details of the reasoned action approach theory and its applicability to this study. Also, I discuss studies related to the significant construct or variables relevant to the study's scope and applicable methodology and method approach.

Chapter 2: Literature Review

Introduction

This study examined the relationship between alternative cost-savings strategies to reduce medication financial burden and predictors of such use among adults with T2D. In other words, this study investigated the association between patients' self-reported monthly OOP expenses, a monthly number of prescribed medication, health insurance status, and utilization of each cost-savings strategy that includes obtaining samples from physicians or patients assistance programs, splitting pills or changing dosage frequency to make medication last longer, purchasing medication from another country, and purchasing from the internet in T2D adults controlling for patient characteristics (socioeconomic and demographics factors).

I tested whether each alternative prescription drug source used to reduce cost is associated with the level of patients' self-reported monthly OOP expenses on their prescribed medication. Also, I examined the associations between the utilization of each cost-savings strategy and self-perceived health insurance status and participants' self-reported number of prescribed medications needed while controlling for patient characteristics (demographics and socioeconomic factors). Specifically, I compared the variables using each cost-savings strategy to understand possible predictors of strategies used.

According to ADA (2018), on average, adults with T2D take at least one or more prescribed medications in managing their chronic illness. Individuals over 65 years old are covered by Medicare supplement Part D, resulting in enormous OOP expenses, which constitute a significant financial burden (ADA, 2018; Brown & McBride, 2015; Musich et al., 2015). This suggests that in healthcare service, having no health insurance or inadequate (poor) health insurance is a challenge for diabetes patients in meeting their medication needs. Given this outcome, other studies reported that patient utilization of alternative sources of prescription drugs (cost-saving strategies) has helped them manage drug cost-related access issues (Cohen & Cha, 2019; Kang et al., 2018; Kleinsinger, 2018; Musich et al., 2015). However, I determined no relationship between the cost-saving strategies used and the specific independent variable considered in this study. However, the impact of the variables may have influenced participants with T2D to use any medication cost-saving strategy.

In the literature review in this chapter, I first address the theoretical foundation for this study. The reason action approach theory helps explain the potential relationship and behavior change using alternative cost-savings strategies (alternative source to obtain prescription medication). The review illustrates and identifies adultT2D patients' specific prescription medication cost-related access barriers (OOP expenses, the number of prescribed medications, and health insurance status) and association with different cost savings strategies among T2D adults. Besides reviewing the association between cost-savings strategies, several cost-related barriers may impact all sectors of healthcare expenditure and services, including private insurers, public programs, and individual patients' characteristics (CMS, 2017). Also, medication nonadherence, demographic and socioeconomic (characteristics), and different cost-saving strategies were reviewed.

For this study, cost-saving strategies are defined as using any alternative source to obtain prescription medication (Musich et al., 2015). Research studies addressed the importance of both trackable and untrackable claim cost-saving strategies to manage prescription medication access and reduce cost. Still, they did not review the impact of cost-related issues and utilization of the untrackable alternative source to obtain medication among adults diagnosed with T2D patients with the specific variables that include OOP expenses, those prescribed with many medications, and their health insurance status.

Literature Search strategies

I searched relevant topics and keywords as the first step in locating materials in the Walden library database. The keywords included *cost-saving strategy* or *method, prescription medication*, *older adult, diabetes, cost-related access, barriers, uninsured, underinsured, out-of-pocket expenses*, *Medicare*, and *health service use*. The extensive search focused on peer-reviewed journals and books published in the past 5 years in the following academic databases used by social science and health service researchers: EBSCO, Google Scholar, and MEDLINE.

Use map strategy is adopted to organize the search for a review (Creswell, 2014), using an excel book or other programming tools. Using this method, I organized the literature according to its usefulness in the study. For example, I used it to understand the proposed research gap and contribution to the existing literature. I created figures and hierarchical structures to represent sections of the map, usually top-down, with the top describing the article and down to the proposed study (Creswell, 2014).

At the top of the map was the topic in a box. Each box underneath is labeled with the search words on the database reviewed on the issues, signifying categories. Inside each box is referencing APA format, illustrating contents and citations that lead to subtopics and sub-subtopics. Each table or branch's size depends on the level or amount of literature available and the depth of exploration. It organized the research into a diagram that shows how the study builds on the investigation.

Theoretical Foundation

The Reasoned Action (TRA) Theory

The Theory of Reasoned Action (TRA) was developed and tested in 1975 by Fishbein and Ajzen (1975). A general human behavior theory explains the relationship between attitudes, beliefs, and behavior. The theory holds that people act reasonably and rationally, while subjective norms influence their judgment. The broader use of TRA in social psychology to predict human behavior ranges has proven the theory to be fundamental and influential. The two elements of the TRA ascertained the core constructs that influenced people's actions or reactions: (1) attitudes (ATT) towards specific behaviors and (2) subjective norms (SNs). According to Ajzen and Fishbein (1980), TRA predicts both a person's attitude and subjective patterns that influence the degree of intent to engage in a specific behavior that predicts acceptance of such action (behavior). Hale et al. (2002) suggested that the belief on which attitude is based are cognitions that link given behaviors.

Thus, for greater theory applicability to enable explanation and prediction of the behavior of an incomplete control (Ajzen ,1985, 1991; La Barbera & Ajzen, 2020), the

TRA was renamed the theory of planned behavior (TPB), adding actual or perceived behavioral control (PBC) to the TRA model. The reasoned action or planned behavior theory posited that intentions predicted behavior to the extent that actual control to perform the behavior is high (Juan et al., 2016; La Barbera & Ajzen, 2020). The PBC is expected to moderate the effects of the ATT and SN in actual BI (Ajzen, 1985, 1991). Besides, Fishbein (2008) argued that in predicting and understanding human behavior in medical and health intervention, the reasoned action approach identifies a set of variables that account for important variance in each behavior. Therefore, he formulated a model that includes reasoned action and planned behavior theory, including the major variables, intention, attitude, perceived norms, self-efficacy, or PBC. In other words, “behavioral beliefs (often referred to as cost-benefits or outcome expectancies), normative beliefs, and control beliefs” are important variables when considering predictors or changes in each behavior (Fishbein, 2008, pg. 835).

Fishbein and Ajzen’s (2010) book entitled *Predicting and Changing human Behavior* cited other studies validating the “reasoned action.” The reasoned action approach model is an understanding of human behavior in that intention mediates performance, and sociodemographic characteristics and three independent variables: (1) ATT, defined as the level at which individual participants concluded that the behavior was the same does benefit them or not at all beneficial, (2) SN, which refers to the belief that others approve or disapprove of the behavior, and (3) PBC, interpreted as the extent to which an individual believes that personal and environmental factors either hinder or progress their efforts to perform the behavior (Fishbein & Ajzen, 2010; Juan et al., 2016).

However, when ATT and SN are favorable, it is believed that the intention to perform a behavior is favorable, i.e., the extent of people's perceived control over the behavior is high (La Barbera & Ajzen, 2020). In other words, together, ATT and SN moderated by PBC shapes an individual BI and behavior (Karimy et al., 2019). Several studies have shown the theory's applicability in predicting intentions (La Barbera & Ajzen, 2020). For example, a study that used items in a national survey of employment, with 557 participants, used the reasoned action approach model including demographic, ATT, SN, and the PBC construct to predict that African Americans and people who are having difficulty meeting financial obligations and not receiving benefits are most likely to have a greater intention to return to work (Jian et al., 2016). The reasoned action approach study predicted that participants are willing to return to work despite their MS condition (Jian et al., 2016). Kennedy and Wilson's (2017) study of 995 participants who purchased pharmaceuticals online revealed a plausible percentage (44.7%) did so on cost considerations, while 37.9% did so at their employer or health plan direction. Another study suggested that 26.3% of adults aged 18-64 diagnosed with diabetes between the year 2017 and 2018 in the United States reported asking their doctor for a lower-cost prescription drug have a positive attitude or willingness to use other alternative cost-saving strategies (Cohen & Cha, 2019), suggesting that behavioral beliefs and outcomes influence one's intention and behavior (Fishbein, 2008).

In addition, researchers in other studies have concluded that the use of alternative sources for prescription drugs are beneficial to managing drug cost-related access issues, such as lack of insurance or being indigent, underinsured, or low-income (Choi et al., 2016; Cohen & Cha, 2019; Cohen & Villarroel, 2015; Kang et al., 2018; Kleinsinger, 2018). Lack of access can worsen the situation and risk of poorer health among diabetes patients (Choi et al., 2016; Kang et al., 2018; Kleinsinger, 2018). However, the use of the alternative source to obtain a low-cost prescription drug, especially the untrackable claim source (that include splitting pills or changing dosage frequency, obtaining free samples from physicians or patients assistance programs, purchasing over the internet, and purchasing from other countries), have been linked to the likelihood of medication nonadherence (Cohen & Cha, 2019; Cohen & Villarroel, 2015; Musich et al., 2015).

Thus, given this access to various sources to obtain low-cost medication and the critical role of the individual decision to select and consume medication needed to maintain their health conditions, investigators employed theories that might affect and change people's behaviors (Karimy et al., 2019). For example, a study was conducted to determine the risk factors associated with self-medication employed planned behavior theory, including the PBC construct of the reasoned action approach. The study revealed that some demographic variables such as age, gender, educational level, and the PBC construct of the theory, such as health insurance status, are significant predictors for self-medication (Karimy et al., 2019). A revelation that the TRA and planned behavior theory model may predict utilization and intentions to use cost-savings strategies among adults with T2D to lessen prescription drug financial burden. The research informed the reasoned action approach model that included the PBC to discuss factors influencing individual change in behavior that predicts patients' access to low-cost prescribed medication and utilizing a cost-saving strategy (predicted behavior) in this study.

Operationalization of Theory

Considering the lack of a theory-based study regarding the predictors of using alternative medication cost-savings strategies among adults with T2D, prescription medications have become a higher financial burden for patients and alternative cost-saving strategies associated with medication non-compliance (Musich et al., 2015). The reasoned action approach identifies a set of variables that account for important variance in a particular behavior (Fishbein, 2008). Thus, the reasoned action approach in this study included intention toward using cost-savings strategy, which explained how the independent variables of interest influenced or predicted the behavior (utilization of cost-savings strategies) among patients with T2D controlling for socioeconomic and demographic factors. For example, PBC is a measure of a participant's belief that is having medical health insurance, which controls the cost of healthcare service (prescription drug), either dependent on the utilization of the cost-savings strategies (Karimy et al., 2019). The individual attitudinal concern and perceived perception of number or medication load may be attributed to using alternative strategies to save the cost of prescription medication such as purchase online (Kennedy & Wilson, 2017) or asking their doctors for an alternative source of medication (Cohen & Cha, 2019; Pallarito, 2018;).

However, this study investigated whether a patient's medical health insurance status, monthly OOP expenses, and the monthly number of prescribed medication (IV) may be a conducive effort to implement intention to use alternative cost-saving strategies and potential predictors of behavior (Jian et al., 2016; Karimy et al., 2019; La Barbera &

Ajzen, 2020). The variables were operationalized with the items in a validated CAHPS survey funded and overseen by the U.S. Agency for Healthcare Research and Quality (AHRQ). The CAHPS survey designed to query patients and consumers to report on and evaluate their experiences and satisfaction with Medicare delivery systems and health services and modified questions relevant to this study reported by Musich et al. (2015) was used to capture survey responses. The reasoned action approach explained intention towards the behavior, with prediction and analysis conducted in the multiple binomial logistic regression model to interpret the results and determine a possible relationship among these study variables.

Using the reasoned action approach or theory that predicts participant health behavior help apply the research results to identify the attributes associated with medication cost-savings strategies and the likelihood of medication non-compliance, making the study useful to the public. I also utilized the theory to explain the potential reasons why adults with T2D patient behavior might change due to barriers encountered accessing prescribed medication and the type of medication cost-savings strategies used. The measures analyzed using the two-part survey questionnaire in this project answer the study survey's research questions, including the three independent variables relevant to this study's objectives: monthly OOP expenses, health insurance status, and the monthly prescribed medication (IV). The second part of the questionnaire also (including dependent variable four items checklist of each cost savings strategy used, Questions 12 and 13 measuring intention to use each cost-saving strategy) focused on each cost savings strategy used in the last 12 months (DV). The first part of the survey (5 items) is the controlling variables that measure respondents' demographics such as sex, race/ethnicity, gender, and socioeconomic factors, such as educational level and income. The multiple and binomial logistic regression analysis models were explored and guided by the reasoned action model (ATT, SN, and PBC) to discuss the possible outcomes.

Overview

With medication usage most significant and essential among the adult T2D population (ADA, 2018) to prevent long-term complications of diabetes, sustaining antidiabetic prescription medication is critical to the treatment and management of the disease (Kleinsinger, 2018). In the use of health services, prescription medication financial burden among adults with diabetes or other chronic disease conditions is highly sensitive to the use of alternative sources (medication cost-saving strategies) to obtain low-cost prescription medication for lack of insurance, underinsured or low-income in managing their conditions (Baicker et al., 2017; Musich et al., 2015). However, this strategy to access low-cost prescription drugs has been associated with medication adherence and prescription medication financial burden (Cohen & Cha, 2019; Cohen & Villarroel, 2015; Musich et al., 2015). In other words, using alternative sources of prescription drugs is beneficial to managing drug cost-related access issues such as lack of insurance, poor or underinsured, or low income in health services. An assertion made with the likelihood that some strategies may link to patient medication non-compliance and poorer health (Choi et al., 2016; Cohen & Villarroel, 2015; Kang et al., 2018; Kleinsinger, 2018; Musich et al., 2015).

While most of the studies have focused on self-reported pharmaceutical cost-savings and disparities in the utilization of cost-savings strategies only when examining participants' medication prescription purchasing patterns and link to medication adherence among Medicare and Medicare supplement populations (Choi et al., 2016; Matzke et al., 2018; Musich et al., 2015; Rafferty et al., 2017). None of the studies examined the relationship between the utilization of different cost-savings strategies to reduce medication financial burden, specifically examining the untraceable claims of alternative sources of prescribed medication and predictors of such use among the adults diagnosed with T2D. The purpose of this study is to investigate the association between patients' self-reported OOP expenses, the number of prescribed medications, insurance status, and utilization of each cost-saving strategy that includes obtaining samples from physicians, splitting pills, purchasing medication from another country, and purchasing from the internet in T2D adults controlling for patient socioeconomic and demographics factors.

Diabetes Prevalence and Cost

Within the United States, 30.3 million people have diabetes: approximately 9.4 % (Center for Disease Control and Prevention [CDC], 2017). Among 65 years or older, 23.1 million have prediabetes, which is three to four times higher than other age groups (CDC, 2017). Thus, increased morbidity and mortality among adults with diabetes results in high healthcare costs and prescription medication use (CDC, 2017; Choi et al., 2016). Diabetes complication is associated with other diseases, such as heart diseases and stroke, known to be the top ten diseases likely to cause disability worldwide (CDC, 2016). In other words, diabetes contributes to other illnesses when left untreated, thus increasing the cost of treatment. Researchers estimated that the cost of diagnosed diabetes in the US would reach $245 billion in 2012, which is an economic burden to society (ADA, 2018). In 2017, outpatients' medication expenses for US adults diagnosed with diabetes were approximately $5,000 annually per capita (ADA, 2018). The Center for Disease Control and Prevention (CDC, 2018) projected that 53.1 million people in the United States will likely have diabetes by 2025. People with T2D are typically older adults, age 50 and above (CDC, 2018). These assumptions are considered an aging population, an increasing number of minority groups are at high risk, and an increase in the life span of people with diabetes (CDC, 2018).

Healthcare Service Utilization and T2D Prescription Medication Management

An essential variable is effective health service use. Thus, lacking access to prescription medication due to financial burdens is significantly associated with medication non-compliance resulting in poor health outcomes (Choi et al., 2016; Toulouse & Kodadek, 2016). Among the uninsured, under-insured, and lower-income older adult diabetic population, prescription medication cost is a significant financial burden for managing their chronic condition (Choi et al., 2016).

Healthcare providers measure their success by providing cost-effective and necessary cost-sharing projects; therefore, they thrive on meeting their patient population’s needs (Shepherd et al., 2014). However, some providers engage in programs designed to treat chronic illness management. Others, including Pharmacists and physicians, collaborate to reduce or save prescription medication costs and improve access to health service utilization (Matzke et al., 2018; Rafferty et al., 2017). For example, 56% of diabetes patients observed under a physician and collaborative pharmacy care reported a considerable improvement in their medication-related health outcomes and health service utilization (Matzke et al., 2018). Indeed, accessing low-cost prescription medication using an alternative source strategy reveals that 15.1% of U.S. residents asked their Physicians for a lower-cost medication in 2013 (Cohen & Villarroel, 2015). In 2017-2018, 42.6% of adults below age 64 diagnosed with diabetes who were uninsured asked their doctor for low-cost prescription medication (Cohen & Cha, 2019). Some pharmacy stores provide medicine to low-income uninsured children and adults at a lower cost. For example, Walmart's retail generic prescription drug program offers $4 prescriptions for people without insurance (30 days) and $10 on 90 days prescriptions, allowing people to qualify for prescription medications to save cost (Walmart, 2019).

Prescription Medication Out–Of–Pocket (OOP) Expenses and T2D

Prescription medications' OOP expenses represent one of the highest healthcare costs in the United States. American consumers expended about $47 billion on such payments in 2012 (Center for Medicaid and Medicare Services [CMS], 2016). The annual cost of care for T2D is estimated to be $182.6 (Garcia et al., 2015). The average medication cost for T2D patients with three or more prescriptions is $70.92 representing less than 50% of the total cost of care in a Mexican population sample (Garcia et al., 2015).

Prescription medication expenses constituted a substantial financial burden for patients managing their chronic conditions (Shepherd et al., 2014; Toulouse & Kodadek, 2016). A higher percentage of people (10.1%) diagnosed with diabetes in the U.S. mostly used prescription medication and experienced higher OOP expenses (Cohen & Cha, 2019). In 2017, outpatients' medication expenses for U.S. adults diagnosed with diabetes were approximately $5,000 annually per capita (ADA, 2018). According to CMS (2017) survey data, among U.S. Medicare beneficiaries' samples in the year 2017, 17% of the total healthcare service ($955,661) is OOP, with the highest ($223,456) on prescription drugs (CMS, 2017). Adults below age 65 spent $8,045 of total healthcare service on prescription drugs (CMS, 2017).

On average, $598 out of $3 909 total prescription drug cost is OOP expenses among Medicare beneficiaries residing in community healthcare services (CMS, 2017). However, adults with six or more conditions spent $7,007 OOP on prescription drugs; those with health conditions ranging from 1 to 5 spent between $1,383 and $5,773 (CMS, 2017). With OOP healthcare service expenditure among the elderly at the top 50% of beneficiaries, it amounts to 91% of this group's total healthcare service expenditure in the U.S (CMS, 2017).

Also, with the implementation of Medicare Part D, a supplement referred to as "Medigap," aimed at helping reduce OOP prescription medication cost, which represented an improvement in pharmaceutical coverage, there is still evidence of a coverage gap (Choi et al., 2016). For instance, older adults Part D beneficiaries with diabetes experienced a decrease of 19.2% in the coverage gap between 2006 and 2011 (Choi et al., 2016), indicating that the financial burden for those without Part D prescription supplements will be higher. The Center for Disease Control and Prevention

(CDC, 2018) projected that 53.1 million people in the United States will likely have diabetes by 2025. The projection may increase morbidity and mortality among older adults with diabetes and result in high healthcare costs and prescription medication use (Center for Disease Control and Prevention [CDC], 2017; Choi et al., 2016). These discrepancies necessitate the investigation that adult T2D patients' self-reported OOP expenses may be a possible predictor of alternative medication cost-savings strategies in this study.

Insurance Status and the Number of Prescribed Medications (T2D)

According to Cohen and Cha (2019), the 2017-2018 survey data revealed that among 10.1 % of US adults diagnosed with diabetes, 46.2 % of younger adults that are uninsured and prescribed medication are more likely to ask their doctor for low-cost medication or used other cost savings strategy than 14% with private insurance or 17.8% with Medicaid coverage. The use of cost reduction strategies among older adults aged over 65 depends largely on insurance coverage options than health insurance status (Cohen & Cha., 2019). Prescription medications constituted a significant financial burden for patients without insurance, worsening their ability to manage their chronic conditions (Shepherd et al., 2014). For example, in the treatment of T2D, 55.9% of all participants who received healthcare in a mobile health van and medication from the pharmaceutical procurement program were prescribed two or more diabetic medications (Touluese & Kodadek, 2016). This suggests that frequent access to prescription medication and affordability may improve patient outcomes without medical health insurance that received medication from a pharmaceutical procurement program (Touluese & Kodadek, 2016). Medication needs are greater among older groups; individuals take about seven unique medications each year, depending on their chronic conditions (CMS, 2017).

Within the Medicare Part D supplement population, between 2001 and 2009, there was a sharp increase among seniors that expressed cost-related access disparities among Whites, Blacks, and Hispanics resulting from low income, an indication of inadequate subsidy level three years after implementation (Chakravarty et al., 2015). Other factors (characteristics), such as socioeconomics (e.g., income, education, etc.), demographics (such as gender, race, etc.), and health status (such as lifestyle behaviors), are less associated with adherence (Musich et al., 2015; Kleinsinger, 2018). Lack of insurance among adult diabetes patients is a prescription medication cost-related access barrier that impacts their health outcomes and medication nonadherence (Kang et al., 2018; Kleinsinger, 2018; Ryan et al., 2014).

Besides, among older adults with diabetes and Part D beneficiaries, those who experienced the coverage gap from 2006 to 2011 decreased by 40.9% from 60.1% in 2006 (Choi et al., 2016). Although Part D supplements' goal is to help reduce OOP prescription medication financial burden, there is still a coverage gap (Choi et al., 2016; MacEwan et al., 2017), especially for those without insurance coverage. To fill the gap, Congress passed the Affordable Care Act (ACA) in 2010 to increase healthcare coverage access by expanding Medicaid program eligibility and subsidizing health plans to address inadequate insurance coverage determinants through health insurance exchange (Adepoju et al., 2019; KFF, 2019). Before this act, uninsured diabetic adults were less likely to access healthcare service use and prescription medication than the insured. However, healthcare service use is more likely to increase (Brown & McBride, 2015).

For example, the Oregon Medicaid expansion health insurance experiment indicated that lack of insurance is still a barrier to accessing prescription medication among adults with chronic illness (Baicker et al., 2017). Although Medicaid expansion among poor adults significantly increases their access to prescription medication used to manage severe conditions (Baicker et al., 2017). A study on the ACA's impact on care access for U.S. adults with diabetes showed that diabetes without health insurance is more likely to have increased complication risk and cost (Brown & McBride, 2015). Therefore, if underinsured, financial assistance for medication remains prevalent despite the landscape of healthcare access providers post-implementation of the ACA in 2010 (Lizheng et al., 2018).

Among Medicare beneficiaries residing in the community, 10% of the overall population reported ever having a prescription fill due to cost; 20% of adults below age 65 reported the same, with 11% of males compared to 9% of females (CMS, 2017). Suggesting that a lack of insurance or inadequate insurance is a factor. For example, PBC is a belief that having no medical health insurance, which controls the cost of healthcare services (prescription drugs), increases the chances of a patient’s self-medication (Karimy et al., 2019). However, the patient’s self-reported medical health insurance status, monthly OOP expenses, and the monthly number of prescribed medication (IV) among adults with T2D investigated in this study was a revelation that these factors are conducive effort to implement intention to use medication alternative cost-saving strategies and potential reasoned action and planned behavior theory predictions (La Barbera & Ajzen, 2020; Jian et al., 2016).

Diabetes Type-2 (T2D) and Alternative Medication Cost Savings Strategies

Diabetes is known to significantly impact the patient's health and ability to perform daily living activities (Bourdel et al., 2019; Cusack et al., 2008). Studies are limited when comparing alternative strategies for obtaining low-cost prescription medication among adults with T2D. None focuses on predictors or intent on utilizing cost-saving strategies among participants or adults with T2D. However, in one study, 25% of older adult respondents with diabetes treated their medical conditions using cost-savings strategies (Musich et al., 2015). The cost-saving strategies used are common among older adults, and Medicare supplements Part D insured to augment their coverage (Cohen & Villarroel, 2015; Musich et al., 2015). Musich et al. (2015) study on pharmaceutical cost-saving strategies in a Medicare supplement population estimated that 25% of the overall survey respondents with diabetes treated medical conditions self-reported using cost-saving strategies. The higher cost of prescription medication constituted a higher financial burden in managing chronic conditions. However, the use of the alternative source to obtain a prescription drug, especially the untrackable source (that include splitting pills, obtaining free samples from physicians, purchasing over the internet, or purchasing from another country), have linked to the likelihood of medication nonadherence (Cohen & Villarroel, 2015; Musich et al., 2015).

With most consumers using cost-saving strategies to reduce medication costs, not all sales of such prescription drugs are reported and tracked by the pharmacy benefit manager on the administrative pharmacy database (Musich et al., 2015). According to Musich et al. (2015), generic drugs, purchasing from retail outlets, and mail orders are generally tracked in the pharmacy administrative database though not included as cost-savings strategies in this study. For example, Walmart’s retail prescription drug program provides $4 prescriptions for people without insurance, 30 days of generic medications, and $10 on 90 days prescriptions, allowing people who qualify for prescription medication to save costs (Walmart, 2019).

Nevertheless, this study’s design of the predictors and the use of each claim's nontrackable cost-saving strategies enables participants to self-report the use and interpret the untrackable claim sources. Therefore, instead of asking participants for other sources, it does not include using generic drugs, purchasing from retail outlets, and mail order as variables. Previous studies were also unable to explain the adherence modeling report on the claim sources (Musich et al., 2015). The use of alternative sources to save prescription medication costs is associated with medication nonadherence (Choi et al., 2016; Kang et al., 2018; Kleinsinger, 2018). A self-reported study reveals that only 73% of self-reported Part D coverage respondents among 92% taking prescription medication had “documented pharmacy claims in the administrative database, discrepancy attributed to underreported medication adherence,” and untrackable claim source (Musich et al., 2015. Pg., 1213).

Purchasing Medication From the Internet

While internet expansion has opened many purchasing options for consumers, purchasing prescription medication is mainly regulated across the developed world. Some countries have been restricted to individuals with a certain age and valid prescription regardless of sales (Kennedy & Wilson, 2017). Despite the regulatory effort, it is optional to report the use of this strategy. Physicians or health insurance coverage plans often direct consumers to a legitimate website (Kennedy & Wilson, 2017). Online or internet chat seeking prescription drug price information may also increase the likelihood of purchasing outside the country (U.S.; Hong et al., 2020).

Interestingly, many consumers that purchased the prescription drug online did so for different reasons. Kennedy and Wilson, 2017surveyed 995 individuals who purchased pharmaceuticals online and found that a plausible percentage (44.7%) did so on cost considerations, while 53.5% of respondents among those who chose other reasons (37.9%) did so at the direction of their employer or health care plan (Kennedy & Wilson, 2017). Most respondents who buy prescribed medication online or purchase medication abroad (international purchase) did so on cost consideration and are not likely to report the unfortunate financial situation or lack of insurance, among other reasons (Cohen & Villarroel, 2015; Kennedy & Wilson, 2017).

Purchasing Medication From Other Countries

According to the National Health Information Survey (NHIS) conducted in 2013, a small percentage (1.6%) of US adults purchase prescription medication from another country. In an analysis of the NHIS 2015- 2017 survey of U.S. adults, among an estimated 152.2 million (18 years above) taking prescription medication, about 2.3 million (1.5%) U.S. individuals purchase medication from another country (Hong et al., 2020). Hong et al. (2020) study indicated that immigrants (3.2, 95% CL) and Hispanic individuals (1.7,95% CL) have a higher odds ratio than being uninsured (3.2, 95% CL) or those born in the U.S. to purchase medication outside the country.

Although this study design does not seek border location or class of drug to estimate Purchase from another country, previous evidence suggested that emergency departments or communities around the U.S. border obtain a high-cost medication class from another country for their patients' given the high cost of the drug in the U.S. (de Guzman et al., 2007). Also, individuals located around the states neighboring Canada and Mexico are likely to cross the border to purchase their prescribed medication (Calvillo & Lal, 2003). The higher cost of prescription drugs in the U.S. than in other countries, notably Canada, prompted the Trump administration to propose a safe importation action policy that allows drug importation from foreign countries and stimulates market competition in the United States (Thomas, 2019). This evidence suggests that purchasing medication from another country outside the U.S. may be an alternative cost-saving strategy.

Split Pills or Changed Dosage Frequency

According to Guerard et al. (2018), cost and outcome have generated significant complexity for patients' compliance with a medication regimen. For instance, half of the 3.2 billion prescribed medications in the U.S. are not taken as directed among patients with asymptomatic illness (Guerard et al., 2018; Zullig et al., 2015). 2017-18 NHIS survey revealed that 17.9 % of the younger adult and 7.2% of adults over 65 diagnosed with diabetes are more likely not to have taken their prescription as directed (Cohen & Cha, 2019). This evidence suggests that not filling a prescription or taking less medicine as directed are ways patients altered their medical care resulting in nonadherence to treatment due to cost (Nipp et al., 2016).

Past studies have previously indicated that pharmacy-prepared split pills may not adversely affect patients' compliance (Fawell et al., 1999). While current studies on the usefulness of splitting pills are limited; however, older adult patients aged 50 and above reported having no problem splitting pills (Peek et al., 2002). Also, Fawell et al. (1999) study of 1617 patients divided into split pills and those who did not split tablets; only 4% of the participants agreed that splitting pills increased their willingness to take medication. It is a revelation that patients will split pills to save them cost or their treatment center (Nipp et al., 2016).

Conversely, diabetes management is multifaceted and needs the patient's compliance with recommended pharmacotherapy for adequate glycemic control. The habit of splitting pills or delaying filling prescriptions is among the primary prescription medication cost-related nonadherence strategies (Goldsmith et al., 2017; Nipp et al., 2016). For example, in a survey interview, 43% of participants reported skipping or splitting pills to cope with costs (Goldsmith et al., 2017). In other words, diabetes patients may use a cost-savings strategy to alter care due to financial burdens or out-of-pocket expenses.

Obtaining Free Samples From Doctors or Patient Assistance Programs

To reduce the cost of prescription drugs, physicians often recommend that uninsured patients get discount cards. In 2013 about 15.1% of U.S. residents asked their Physicians for a lower-cost medication, and others (4.2%) sought alternative therapies to save cost (Cohen & Villarroel, 2015). Besides, 26.3% of younger adults aged under 65 were diagnosed with diabetes, and 21.9% of those over 65 asked their physicians for lower-cost medication between 2017 and 2018 in the U.S. (Cohen & Cha, 2019). Some organizations offer a discount card that will be redeemed up to 80% on prescription drugs at the pharmacy, especially when paying cash instead of insurance (Pallarito, 2018). Pharmacy stores also provide medication to low-income uninsured children and adults at a lower cost.

About 50% of the overall Medicare population reported using free samples from their physicians, higher than 39.6% of those in Medicare supplement insured (Musich et al., 2015). However, minorities, females, and lower educational level patients are less likely to use a cost-savings strategy or request free samples from their physicians. The evidence suggests a shared attitude among older adults with low income who used prescription medication cost-savings strategies (Musich et al., 2015). This revelation provides the need to investigate further the relationship between alternative medication cost-saving strategies and individual and other characteristics that predicted the use of the strategies among participants in this study.

Individual Characteristics or Factors That Impact the Utilization of Cost-Saving Strategies and T2D

Factors such as demographics (e.g., race/ethnicity, gender.), socioeconomic factors (income, education), and health literacy or lifestyle may influence the outcome of this study (Musich et al., 2015). Among participants in a Medicare supplement population - groups most likely to use cost-saving strategies are white, male, educated with more chronic conditions, and employ more medication and splitting pills (Musich et al., 2015). Among U.S. women diagnosed with diabetes between 2017 and 2018, 14.9 % and 11.6% of men reported not taking their medication as prescribed due to cost (Cohen & Cha, 2019). However, minorities with lower education and low socioeconomic status are less likely to use cost-saving strategies (Cohen & Villarroel, 2015). Musich et al. (2015) suggested that different groups are most likely to use cost-saving strategies, factoring in demographics and socioeconomic status. Among survey respondents are white (85.2%), Male (44.1%), educated (31%, 4year college or more) with a more chronic condition, and tend to use more medication and splitting pills (Musich et al., 2015). Also, minorities with lower education and low socioeconomic status are less likely to use cost-saving strategies (Musich et al., 2015). The demographic and socioeconomic factors are compared as controlling or mediating factors to using strategy to obtain low-cost medication among individuals with T2D participating in this study.

While income or socioeconomic status remains significant in accessing health insurance (Adepoju et al., 2019; Cohen & Villarroel, 2015; KFF, 2019), lack of insurance or inadequate insurance among adult diabetes patients is a significant medication cost-related barrier impacting patients' health outcomes and medication nonadherence (Kang et al., 2018; Kleinsinger, 2018; Ryan et al., 2014). Researchers also suggested that some of these alternative sources to save prescription medication costs are associated with medication nonadherence, impacting older adults' health outcomes with diabetes (Choi et al., 2016; Kang et al., 2018; Kleinsinger, 2018). In 2017 -2018, almost 7.2% of U.S. adults over 65 years diagnosed with diabetes were not likely to have taken their medication to save costs (Cohen & Cha, 2019). However, 35.7% of younger adults aged below 65 who lack health insurance coverage are more likely not to have taken their medication as prescribed than 17.8% of those on Medicaid or 14.0% of those with private insurance (Cohen & Cha, 2019). Also, the National Center for Health Statistics (NCHS) data (2015) shows that nearly 8% of adults across the country did not take their medication as prescribed due to cost. To save money on prescription medication, patients adopt several strategies, and some are the most common strategies practiced among those who lack health insurance coverage (Cohen & Villarroel, 2015; Pallarito, 2018; Musich et al., 2015). For example, 14.0% of U.S. adults aged below 64 practiced strategies for lack of health insurance coverage (Cohen & Villarroel, 2015). Also, they are likely not to have taken their medication as prescribed. Compared to 10.4% of those on Medicaid or 6.1% of those on private insurance are in this group (Cohen & Villarroel, 2015). However, almost 4.4% of adults aged 65 and over are not likely to have taken their medication to save costs (Cohen & Villarroel, 2015).

Medication Non-Compliance and Alternative Medication Cost-Saving Strategies

Medication adherence interventions aim to improve the quality of life among the person with diabetes and reduce care costs (Andrews et al., 2017; Guerard et al., 2018; Nerat et al., 2016; Zullig et al., 2015). With diabetes complications requiring multifaceted management, the need for patient compliance with recommended pharmacotherapy is vital for adequate glycemic control (Guerard et al., 2018). Due to higher prescription medication costs, patients use strategies to reduce costs. The approach may include splitting pills or delayed filling a prescription reported as contributing sources to prescription medication cost-related nonadherence strategy (Goldsmith et al., 2017; Nipp et al., 2016). For example, Goldsmith et al. (2017) studied patients' experience of cost-related nonadherence (CRNA) to prescription medication. They found that 43% of participants interviewed reported skipping or splitting pills to cope with cost. In other words, diabetes patients use strategies to deal with care due to financial burdens or out-of-pocket expenses. Such an approach is referred to as care altering coping strategy due to treatment financial distress in cancer patients (Nipp et al., 2016).

Cohen and Villarroel (2015) found that nearly 8% of adults across the U.S. did not take their medication as prescribed due to cost, further suggesting that patient compliance with a medication regimen is related to cost and outcome (Guerard et al., 2018). However, frequent access to prescription medication and affordability improve uninsured patients with T2D (Toulouse & Kodadek, 2016). Studies on improving diabetes medication found that half of the 3.2 billion prescribed medications in the U.S. are not taken as directed among patients with asymptomatic illness (Guerard et al., 2018; Zullig et al., 2015). The evidence suggests that not filling a prescription or taking less of an order not as directed are ways patients altered their medical care due to cost resulting in nonadherence to treatment (Nipp et al., 2016). Some cost-saving strategies are already likely to result in unreported medication nonadherence (Musich et al., 2015). The rate of medication nonadherence is mostly sensitive to prescription drug cost-savings strategies (Musich et al., 2015). They are consistently associated with adverse health outcomes, including emergency rooms and hospitalization (Cohen & Villarroel, 2015). Other factors (characteristics), such as socioeconomics (e.g., income, education, etc.), demographics (such as gender, race, etc.), and another health status (such as lifestyle behaviors), are less associated with adherence (Kleinsinger, 2018; Musich et al., 2015).

Thus, nontrackable cost-savings strategies such as purchasing on the internet or in other countries are more likely to predict nonadherence (Musich et al., 2015). Adult T2D patients may use a cost-savings strategy to cope with the prescription medication financial burden and may experience medication nonadherence as a side effect (Cohen & Villarroel, 2015; Musich et al., 2015). However, the relationship between these strategies and variables in this study is essential to understand further the route of medication nonadherence in patients that use the strategy.

Summary and Transition

Most of the existing studies in this domain have focused on self-reported pharmaceutical cost-savings and disparities in the utilization of cost-savings strategies only when examining medication prescription purchasing patterns and link to medication adherence among Medicare and Medicare supplement populations (Choi et al., 2016; Matzke et al., 2018; Musich et al., 2015; Rafferty et al., 2017). None of the studies so far have examined the relationship between the utilization of different cost-savings strategies to reduce medication financial burden, specifically examining the untraceable claims of alternative sources of prescribed medication and predictors (Monthly OOP expenses, number of prescribed medication, insurance status (IV) of such use among the adult T2D controlling for socioeconomic and demographics.

The cost-saving strategies (untraceable claim alternative sources to obtain prescription medication) are dependent variables used in this study. They include taking a free sample from physicians or patient's assistant programs, purchasing from another country, purchasing on the internet, splitting pills, or changing dosage frequency. Researchers have consistently linked the likelihood of medication non-compliance (nonadherence) and the benefits of reducing medication's financial burden to these variables (Cohen &Cha, 2019; Cohen & Villarroel, 2015; Musich et al., 2015). However, this study investigated the association between specific independent variables (patients' self-reported OOP expenses, the number of prescribed medications, health insurance status) and utilization of each cost-saving strategy (DV) in T2D adults while controlling for patient socioeconomic and demographic factors. The result addressed this gap in the literature.

Using the reasoned action approach theory to explain and analyze the logistic regression model to describe the relationship that predicts the outcome makes an original contribution. It expands our knowledge of health services and behavioral practice. Therefore, contributes to understanding how alternative medication sources impact health services and prescription medication costs among the T2D population. The next chapter (3) discusses the study's research method, including the study research design, research questions and hypotheses, data collection methods, population samples or participants, power analysis of sample size, and data analysis. The next chapter also discussed the ethical considerations for this study.

Chapter 3: Research Method

Introduction

This quantitative, cross-sectional survey designed study investigated the association between patients' self-reported OOP expenses, the number of prescribed medications, health insurance status, and utilization of each cost-saving strategy among T2D adults. This study objective examined whether the patients' self-reported OOP expenses, the number of prescribed medications, health insurance status (IV) predict utilization of each prescription drug cost-saving strategy defined as dependent variables (DV) while controlling for demographic and socioeconomic factors among adults with T2D. The independent variables (IV), covariates represent the reasoned action approach theory that predicts intention to use one or more alternative cost-savings strategies (DV; Jian et al., 2016; Karimy et al., 2019). This chapter discusses the research design and method, including details about the population, sampling procedure, primary data collection method, instrumentation, variables, data analysis plan, threats to validity, and ethical considerations.

Research Design and Rationale

The alternative cost-saving strategies dependent variable in this study are defined as sources to obtain medication that includes the untrackable claim source: obtaining free samples from doctors or patient assistance programs, splitting pills or changing dosage frequency, purchasing over the internet, and purchasing from other countries (DV). The IVs measured are the participants' responses to the survey questions relevant to this study about monthly OOP expenses, monthly number of prescribed medications, and health insurance status. Also measured are respondents' responses to questions on demographics (gender/age/race-ethnicity) and socioeconomic factors (income/education; CV), which could influence the study outcome among patients with T2D.

This study used a quantitative, primary data, cross-sectional patients self-reported survey designed and administered online in the Qualtrics platform. The questionnaire was captured in the validated CAHPS survey (2018), and modified questions reported by Musich et al. (2015) to examine the study variable's relationships. The survey was descriptive and restricted to adult U.S. residents with self-reported diagnosed T2D (age 18 years or more) who used a prescription medication in the last 12 months. The design is used to explore how participants' self-reported socioeconomics factors (income, education) and demographics (gender, race, age; co-variables) influence the observed relationship among the variables. Thus, it contributed to society's understanding of the relationship between the variables considered in the study.

The design method was chosen for this study because it enables the researcher to test the objective theories explaining the relationship between multiple variables (Creswell, 2014). The study used the multiple and binomial logistic regression model to analyze the variables that predict participants' intention and utilization of each alternative medication cost-saving strategy. The reasoned action approach (theory) model predictions were used to explain how participants' responses to the survey questions that measure the independent variables (on a scale score, ordinal or dichotomous) may predict the use of each medication alternative's cost-savings strategies (DV; Jian et al., 2016, Karimy et al., 2019) and advanced knowledge in the health service and behavioral practice.

Methodology

Population

This study's target population is U.S. residents 18 years of age and older with self-reported T2D conditions (diagnosed) and who have been prescribed any medication in the last 12 months. While the target population size is unknown, the sample size is estimated to be 385 respondents.

Sampling and Sampling Procedures

Participants are individuals from across the United States recruited through internet Mechanical Turk membership (mTurk). Participants were selected via random sampling of online mTurk members in the United States that meet the inclusion criteria. The mTurk member is a diverse population of individuals working to earn only on a task that interests them. However, this sampling strategy restricted the survey to U.S. residents who are mTurk members, enabling me to maximize the scope of the population.

The participants first received an invitation that detailed information about the study online (through AMTCM). If interested in participation and meeting the qualification criteria, they were directed to click the survey code at the mTurk platform. From there, they were directed to the Qualtrics platform survey and completed an informed consent form to start the survey. Informed consent provides information about the study with enough time to review it before accepting or declining to participate in the study. Clicking a button to consent automatically saved the response.

The sampling strategy included eligibility criteria (referred to as qualification) for participants (members of the AMTCM). The potential participants (AMTCM members) that met the requester (researcher) qualification, including U.S. residents aged 18 years or older, self-reported diagnosed T2D condition who used any prescribed medication in the last 12 months. However, for better relative inference to detect statistical significance between groups at $p < 0.05$, 385, survey respondents are needed (Qualtrics, 2020). The target participants' number set (adult, 18 years and above, diagnose T2D and use any prescription medication to manage the condition - eligibility criteria) allows oversampling of those with more health and prescription medication needs for their diabetic care.

Sample Size - Power Analysis

The study tested a model that comprises multiple predictors (Lund Research, 2018). According to Toulouse and Kodadek (2016), the general conventions of health science and health services research literature indicate statistics significantly be set to the level of 0.05 ($p < 0.05$) (Karimy et al., 2019). The equation could be solved if p is known to determine the sample size. However, in this statistical study test, the largest possible size occurs if only $p=.5$ Standard deviation (Remler & Ryzin, 2011; Qualtrics, 2020).

Using the Qualtrics power analysis computing software, the required sample size for this study in multiple binomial logistic regression statistical test from the equation:

Sample size = (Z-score) 2 * StdDev*(1-StdDev) / (margin of error) 2

Assuming unknown population size. To answer all the research questions:

The confidence interval was 95% level = 1.96 = Z score = .05 at 0.0 (tenth), .5 standard deviation and margin of error = +/- 5%.

From the equation = ((1.96)2 x .5(.5)) / (.05)2,

= 3.8416 x .25 / .0025,

Which equals 0.9604 / .0025 = 384.16.

= 385 respondents are needed = sample size for all research questions.

Procedures for Recruitment, Participation, and Data Collection

The prospective participants were contacted online via their membership on AMTCM with an algorithm that restricted and tracked U.S. residents. U.S. residents identified mTurk members were provided information about survey availability and incentive (stipend) for completing the survey. The member clicks a survey link and reads the instruction (invitation letter). However, members can opt-in only when they meet the inclusion criteria. The incentive or stipends ($1.00) are token compared to what members usually get paid. Once the participant accepts the request to participate by clicking on the survey code, the participants are linked to the Qualtrics platform.

Participation in the research survey is considered optional. Members of workers who received the invitation can take their time to decide about participation within the frame at which the survey is open, given the research topic and overly invasive screening (oversampling those with more intensive health needs). Once on the Qualtrics platform, informed consent is displayed. The participant who clicks agreed will continue. However, the sampling strategy included questions in the survey questionnaire to further screen for eligibility criteria and mTurk minimum participation age (18+ years old) and requester qualification that participants self-reported diagnosed T2D and used any prescribed medication in the last months when answer yes will continue. A code is generated (not for participants' information but to acknowledge the survey completion). The code was presented to the AMTC after survey completion for payments. Three days were granted to the requester to either accept the survey response or reject it. Participants would not be reimbursed if the data were not valued (i.e., incomplete) and rejected. Those who did not answer the survey questions (6 and 7) on diabetes or not taking prescription medication in the last 12 months were not counted. The data collection process was scheduled for 30 days or until the accepted responses (400 respondents to increase power) or completed surveys reached the expected number of participants. All stipends or fees paid for this data collection are for AMTCM and Qualtrics, including administrative and respondents' fees.

Instrumentation and Operationalization of Constructs

The CAHPS Survey

The CAHPS Survey (CAHPS –ACOs- Survey 2018 CAHPS® Survey for Accountable Care Organizations [ACOs] participating in Medicare Initiatives): Validated Consumer Assessment of Healthcare Providers and Systems (CAHPS) survey funded and overseen by the U.S. AHRQ was adapted for this study. The survey investigation is the national healthcare standard for measuring a patient's healthcare services experience and is available in the public domain. The CAHPS questionnaire was designed for patients and consumers to report and evaluate their skills and satisfaction with Medicare delivery systems (CAHPS, 2018). The validity and reliability of the self-reported CAHPS survey and questions captured and designed online for this study were previously reported in Musich et al.'s (2015) study on "Pharmaceutical Cost-Saving Strategies and their Association with Medication Adherence in a Medicare Supplement Population" (publicly available, author permission to modified). The survey (Appendix A) section (Part 1) consists of five questions that measure patients' demographics (age, race, gender), socioeconomic factors (income, education), and two questions needed to filter the sample in the study. Section 2 (Part 2) consists of six questions (8-13) that measured variables relevant to this study objective:

1. "In the last month, how many medications, including those you were already taking, and any new medications prescribed for your diabetes?"

- ☐ 9 or more
- ☐ 7 - 8
- ☐ 5 - 6
- ☐ 3 - 4
- ☐ 1 – 2
- ☐ None

2. Do you have health insurance?

- ☐ Yes
- ☐ No

3. "Please mark the type of health insurance you have."

- ☐ Medicaid
- ☐ Veteran's benefits
- ☐ Employer Insurance
- ☐ Union or Retire health coverage

□ Medicare prescription plan

□ Affordable Care Act (ACA) or Medicaid Expansion

□ Other private insurance/not sure

4. What are your monthly average prescription drug out-of-pocket (OOP) expenses for your condition?

1. $481- above

2. $116-481

3. $115 – 110

4. $ 110 – 51

5. $50 - below

5. Check all that apply; "In the last twelve months, did you use any of the following to save money on your prescription medication?"

- Purchase medication over the internet
- Purchase medication from other countries
- Obtain free samples from doctors or patients assistance program
- Split pills or changed the dosage frequency

The dependent variables investigated in this study have consistently revealed the impact of medication adherence due to the underreporting measure of non-adherence of this strategy among the Medicare Part D supplement population (Musich et al., 2015). Building on the literature's revelation and examination, additional survey questions (construct) relevant to this study were added to measure participants' intention to use medication alternative cost-saving strategy variables (Appendix A, Survey Question 13). The approach also reported in Jian et al. (2016) study (publicly available):

"In the last 12 months, when you could not afford all the medications for your diabetes, what are you likely to do?"

- Purchase medication over the internet
- Purchase medication from other countries
- Obtain free samples from doctors or patients assistance program
- Split pills or changed the dosage frequency

Thus, in this study, patient's health insurance status, OOP expenses as measured via CMS claim (2017), and the monthly number of prescribed medication (IV) were considered a conducive effort to implement intention to use alternative cost-saving strategies (DV) and potential TRA and TPB predictions (Jian et al., 2016; Karimy et al., 2019; La Barbera & Ajzen, 2020).

Operationalization

The self-reported patients' online survey responses operationalize all the variables — the survey attached as Appendix A to this document was used to collect the data. The DVs indicating survey participant's response, Part 2 of the questionnaire, included the four items checklist. Question 12 operationalize each cost savings strategy participants actually "Used or not Used" over the last 12 months. Question 13 operationalize the cost-savings strategy participant intent (or likely) to use in the future. This study's cost-saving strategies are defined as using any of the untraceable claims of alternative medication cost-saving sources: purchase medication over the internet, purchase medication from another country, obtain free samples from doctors or patient's assistance programs, and split pills or change dosage frequency. However, other sources or something else is not operationalized in this study's analysis because they were often trackable claims or reported in another category (Musich et al., 2015).

The three independent variables (IV), including the respondent's response to questions (8-11) on out-of-pocket (OOP) expenses, numbers of prescribed medication, and health insurance status, are operationalized as predictors in this study. The covariate variables (survey questions 1-5), including demographics (age, race, gender) and socioeconomic (Income; education), operationalize as characteristics or factors influencing the outcomes. However, participants' responses to diabetes and prescription medication (questions 6 and 7) are not operationalized as a variable but included in the survey to filter or screen samples in this study.

The dependent variable (DV) intention to use the cost-savings strategy (question 13) operationalize based on four items composite scale score designed on 5 points Likert scale ranging from "1-extremely unlikely" to "5-extremely likely" (Jian et al., 2016). The individual dependent variable is measured at a continuous level (i.e., composite scale score from 1 to 5). The patient's self-reported utilization of each Cost-savings strategy (question 12) is operationalized as a checklist of actual "Used" or "Not Used" in the last 12 months. Thus, measured separately on a dichotomous scale, "Used" coded "1" and "Not Used" coded "2".

The independent and covariable variables are measured as continuous (i.e., an interval or ratio variable) or categorical (i.e., an ordinal or nominal variable). The participant's responses to monthly OOP expenses (5 item scale ratio, measured in U.S. dollars, corresponding to CMS (2017) prescription drug OOP claim measured as ordinal but ranked as continuous variables), the monthly number of prescribed medications (6 item scale ratio, measured in the number of prescribed medication, corresponding to the value reported in the year 2017 Medicare healthcare service prescription drug beneficiary survey data), measured as ordinal but ranked as continuous variables in this study, age (measured in years), income (measured in U.S. dollars) and education (measured on scale ratio 1 to 5) are continuous scale level. The response to the questions on health insurance status (Two categories: Yes and No, "Yes" coded "1" and "No" coded "2"), type of insurance (Seven categories-checklist: Medicaid, Veteran's benefits, Employer Insurance, Union or Retire health coverage, Medicare prescription plan, Affordable Care Act (ACA) or Medicaid Expansion, Other private insurance/not sure) not coded for analysis, Gender (Two categories: male and female, "Male" coded "1" and "female" coded "2"), Race-ethnicity (three categories: White, Black or African American and Latino ethnic background, "White" coded "1" and "Black or African American" coded "2" but Latino ethnic background are not coded nor included in the analysis) are measured on a nominal scale.

Data Analysis Plan

The first step I took in the analysis plan was data cleaning, including coding, entry, and checking for missing data. The data obtained from the completed questionnaires were then analyzed using SPSS version 27.0. Multiple and binomial logistic regression statistics answered the research questions or hypothesis testing (Table

1). The propensity weighing multiple logistic regression for survey non-response bias was proposed to determine or adjust for potential survey response selection bias for generalizability of the outcome. Instead, I conducted a Cronbach's alpha procedure on SPSS statistics to measure internal consistency (reliability) in participants' responses to the construct reflecting different underlying factors that employed the questionnaire on all samples. This approach's utility in determining survey selection bias and reliability was reported in Jian et al. (2016) and Karimy et al. (2019).

Research Questions and Hypothesis

RQ1a: What is the association between the monthly out-of-pocket (OOP) expenses and Purchase of medication over the internet in Type-2 Diabetes (T2D) adults while controlling for patient socioeconomic and demographics?

> ***H_o*1a:** There is no association between the monthly OOP expenses and Purchase of medication over the internet in T2D adults while controlling for patient socioeconomic and demographics.
>
> ***H_I*1a:** There is an association between the monthly OOP expenses and Purchase of medication over the internet in T2D adults while controlling for socioeconomic and demographics.

RQ1b: What is the association between the monthly out-of-pocket (OOP) expenses and Purchase of medication from other countries in Type-2 Diabetes (T2D) adults while controlling for patient socioeconomic and demographics?

***H_o*1b:** There is no association between the monthly OOP expenses and Purchase of medication from other countries in T2D adults while controlling for patient socioeconomic and demographics.

***H_1*1b:** There is an association between the monthly OOP expenses and Purchase of medication from other countries in T2D adults while controlling for patient socioeconomic and demographics.

RQ1c: What is the association between the monthly out-of-pocket (OOP) expenses and Obtaining free samples from doctors or patient assistance programs in Type-2 Diabetes (T2D) adults while controlling for patient socioeconomic and demographics?

***H_o*1c:** There is no association between the monthly OOP expenses and Obtaining free samples from doctors or patient assistance programs in T2D adults while controlling for patient socioeconomic and demographics.

***H_1*1c:** There is an association between the monthly OOP expenses and Obtaining free samples from doctors or patient assistance programs in T2D adults while controlling for patient socioeconomic and demographics.

RQ1d: What is the association between the monthly out-of-pocket (OOP) expenses and Splitting pills or changing dosage frequency in Type-2 Diabetes (T2D) adults while controlling for patient socioeconomic and demographics?

***H_o*1d:** There is no association between the monthly OOP expenses and Split pills or change dosage frequency in T2D adults while controlling for patient socioeconomic and demographics.

***H*₁1d:** There is an association between the monthly OOP expenses and Split pills or change dosage frequency in T2D adults while controlling for patient socioeconomic and demographics.

RQ2a: What is the association between the monthly number of prescribed medications and Purchase of medication over the internet in Type-2 Diabetes (T2D) adults while controlling for patient socioeconomic and demographics?

H_o2a: There is no association between the monthly number of prescribed medications and Purchase of medication over the internet in T2D adults while controlling for patient socioeconomic and demographics.

$H_1$2a: There is an association between the monthly number of prescribed medications and Purchase of medication over the internet in T2D adults while controlling for patient socioeconomic and demographics.

RQ2b: What is the association between the monthly number of prescribed medications expenses and Purchase of medication from other countries in Type-2 Diabetes (T2D) adults while controlling for patient socioeconomic and demographics?

H_o2b: There is no association between the monthly number of prescribed medications and Purchase of medication from other countries in T2D adults while controlling for patient socioeconomic and demographics.

$H_1$2b: There is an association between the monthly number of prescribed medications and Purchase of medication from other countries in T2D adults while controlling for patient socioeconomic and demographics.

RQ2c: What is the association between the monthly number of prescribed medications and Obtaining free samples from doctors or patient assistance programs in Type-2 Diabetes (T2D) adults while controlling for patient socioeconomic and demographics?

***H_o*2c:** There is no association between the monthly number of prescribed medications and Obtaining free samples from doctors or patient assistance programs in T2D adults while controlling for patient socioeconomic and demographics.

***H_1*2c:** There is an association between the monthly number of prescribed medications and Obtaining free samples from doctors or patient assistance programs in T2D adults while controlling for patient socioeconomic and demographics.

RQ2d: What is the association between the monthly number of prescribed medications and Split pills or change dosage frequency in Type-2 Diabetes (T2D) adults while controlling for patient socioeconomic and demographics?

***H_o*2d:** There is no association between the monthly number of prescribed medications and Split pills or change dosage frequency in T2D adults while controlling for patient socioeconomic and demographics.

***H_1*2d:** There is an association between the monthly number of prescribed medications and Split pills or change dosage frequency in T2D adults while controlling for patient socioeconomic and demographics.

RQ3a: What is the association between the health insurance status and Purchase of medication over the internet in Type-2 Diabetes (T2D) adults while controlling for patient socioeconomic and demographics?

***H*o3a:** There is no association between the health insurance status and Purchase of medication over the internet in T2D adults while controlling for socioeconomic and demographics.

***H*l3a:** There is an association between the health insurance status and Purchase of medication over the internet in T2D adults while controlling for socioeconomic and demographics.

RQ3b: What is the association between the health insurance status and Purchase of medication from other countries in Type-2 Diabetes (T2D) adults while controlling for patient socioeconomic and demographics?

***H*o3b:** There is no association between the health insurance status and Purchase of medication from other countries in T2D adults while controlling for patient socioeconomic and demographics.

***H*l3b:** There is an association between the health insurance status and Purchase of medication from other countries in T2D adults while controlling for patient socioeconomic and demographics.

RQ3c: What is the association between the health insurance status expenses and Obtaining free samples from doctors or patient assistance programs in Type-2 Diabetes (T2D) adults while controlling for patient socioeconomic and demographics?

***H*$_o$3c:** There is no association between the health insurance status and Obtaining free samples from doctors or patient assistance programs in T2D adults while controlling for patient socioeconomic and demographics.

***H*$_l$3c:** There is an association between the health insurance status and Obtaining free samples from doctors or patient assistance programs in T2D adults while controlling for socioeconomic and demographics.

RQ3d: What is the association between the health insurance status and Split pills or change the dosage frequency in Type-2 Diabetes (T2D) adults while controlling for patient socioeconomic and demographics?

***H*$_o$3d:** There is no association between the health insurance status and Split pills or change the dosage frequency in T2D adults while controlling for patient socioeconomic and demographics.

***H*$_l$3d:** There is an association between the health insurance status and Split pills or change the dosage frequency in T2D adults while controlling for patient socioeconomic and demographics.

RQ4a: What is the association between the insurance status, monthly out-of-pocket (OOP) expenses, monthly number of prescribed medication, and Purchase of medication over the internet in Type-2 Diabetes (T2D) adults while controlling for patient socioeconomic and demographics?

H$_l$4a: There is an association between the insurance status, monthly out-of-pocket (OOP) expenses, monthly number of prescribed medication, and Purchase of medication over the internet in T2D adults while controlling for patient socioeconomic and demographics.

H_o4a: There is no association between the insurance status, monthly out-of-pocket (OOP) expenses, monthly number of prescribed medication, and Purchase of medication over the internet in T2D adults while controlling for patient socioeconomic and demographics.

RQ4b: What is the association between the insurance status, monthly out-of-pocket (OOP) expenses, monthly number of prescribed medication, and Purchase of medication from other countries in Type-2 Diabetes (T2D) adults while controlling for patient socioeconomic and demographics?

H_l4b: There is an association between the insurance status, monthly out-of-pocket (OOP) expenses, monthly number of prescribed medication, and Purchase of medication from other countries in T2D adults while controlling for patient socioeconomic and demographics.

H_o4b: There is no association between the insurance status, monthly out-of-pocket (OOP) expenses, monthly number of prescribed medication, and Purchase of medication from other countries in T2D adults while controlling for patient socioeconomic and demographics.

RQ4c: What is the association between the insurance status, monthly out-of-pocket (OOP) expenses, monthly number of prescribed medication, and Obtaining free samples from doctors or patient assistance programs in Type-2 Diabetes (T2D) adults while controlling for patient socioeconomic and demographics?

H$_l$4c: There is an association between the insurance status, monthly out-of-pocket (OOP) expenses, monthly number of prescribed medication, and Obtaining free samples from doctors or patient assistance programs in T2D adults while controlling for patient socioeconomic and demographics.

H$_o$4c: There is no association between the insurance status, monthly out-of-pocket (OOP) expenses, monthly number of prescribed medication, and Obtaining free samples from doctors or patient assistance programs in T2D adults while controlling for patient socioeconomic and demographics.

RQ4d: What is the association between the insurance status, monthly out-of-pocket (OOP) expenses, the monthly number of prescribed medication, and Split pills or change the dosage frequency in Type-2 Diabetes (T2D) adults controlling for patient socioeconomic and demographics?

H$_l$4d: There is an association between the insurance status, monthly out-of-pocket (OOP) expenses, the monthly number of prescribed medication, and Split pills or change the dosage frequency in T2D adults while controlling for patient socioeconomic and demographics.

H$_o$4d: There is no association between the insurance status, monthly out-of-pocket (OOP) expenses, the monthly number of prescribed medication, and Split pills or change the dosage frequency in T2D adults controlling for patient socioeconomic and demographics.

Statistical Analysis

All the research questions were answered (Table 1 below): All data analyses were conducted according to the pre-established plan in SPSS version 27.0. The statistically significant level was set at 0.05. This approach was reported in Karimy et al. (2019).

Table 1

Summary table of research questions, statistical test, and operational measure

Research Questions	Statistical Test	Operational measure
RQ1a	binomial logistic regression statistics test the significance of the association between the monthly OOP expenses (IV) and odds of Purchasing medication over the internet (DV) over the last 12 months controlling for socioeconomics and demographics.	DV, participants' responses to survey question 12, four items checklist, (Purchase medication over the internet) “Used” coded “1” or “Not Used” coded “2” over the last 12 months. IV, the respondent’s response to questions (11) on OOP expenses(5 item scale ratio, measured in U.S. dollars measured as ordinal but ranked as continuous variables, coded “1” highest to “5” lowest). CV, controlling factors participants response to Survey questions (1-5) - demographics (Race, two categories: “White” coded “1” and “Black or African American” coded “2”), Age, measured in years), Gender, two categories: “Male” coded “1” and “female” coded “2”),) and socioeconomic (Income, measured in U.S. dollars and education, measured on a scale ratio 1 to 5) are continuous scale level Coded highest “1” to Lowest “5”).
RQ1b	binomial logistic regression statistics test the significance of the association between the monthly OOP expenses (IV) and odds of Purchasing medication from other countries (DV), controlling for demographics (Race, Age, Gender) and socioeconomic (Income, Education) variables.	DV, participants’ responses to survey question 12 four items checklist, (Purchase medication from other countries) “Used” coded “1” or “Not Used” coded “2” over the last 12 months. IV, the respondent’s response to questions (11) OOP expenses (5 item scale ratio, measured in U.S. dollars measured as ordinal but ranked as continuous variables, coded “1” highest to “5” lowest).
RQ1c	binomial logistic regression statistics test the significance of the association between the monthly OOP expenses (IV) and odds of Obtaining free samples from doctors or patient assistance programs (DV), controlling for demographics (Race, Age, Gender) and socioeconomic (Income, Education) variables.	DV, participants’ responses to survey question 12 four items checklist, (Obtained free samples from doctors or patient assistance programs) “Used” coded “1” or “Not Used” coded “2” over the last 12 months. IV, the respondent’s response to questions (11) OOP expenses (5 item scale ratio, measured in U.S. dollars measured as ordinal but ranked as continuous variables, coded “1” highest to “5” lowest).

RQ1d	Binomial logistic regression statistics test the significance of the association between the monthly OOP expenses (IV) and odds of Splitting pills or changing dosage frequency (DV), controlling for demographics (Race, Age, Gender) and socioeconomic (Income, Education) variables.	DV, participants' responses to survey question 12 four items checklist, (Split pills or change dosage frequency) "Used" coded "1" or "Not Used" coded "2" over the last 12 months. IV, the respondent's response to questions (11) OOP expenses (5 item scale ratio, measured in U.S. dollars measured as ordinal but ranked as continuous variables, coded "1" highest to "5" lowest).
RQ2a	Binomial logistic regression statistics test the significance of the association between the monthly number of prescribed medications (IV) and odds of Purchasing medication over the internet (DV), controlling for demographics (Race, Age, Gender) and socioeconomic (Income, Education) variables.	DV, participants' responses to survey question 12 four items checklist, (Purchase of medication over the internet) "Used" coded "1" or "Not Used" coded "2" over the last 12 months. IV, the respondent's response to questions (8) monthly number of prescribed medications (6 item scale ratio, measured as ordinal but ranked as continuous variables, coded "1" highest to "6" lowest).
RQ2b	Binomial logistic regression statistics test the significance of the association between the monthly number of prescribed medications (IV) and odds of Purchasing medication from other countries (DV), controlling for demographics (Race, Age, Gender) and socioeconomic (Income, Education) variables.	DV, participants' responses to survey question 12 four items checklist, (Purchase of medication from other countries) "Used" coded "1" or "Not Used" coded "2" over the last 12 months. IV, the respondent's response to questions (8) monthly number of prescribed medications (6 item scale ratio, measured as ordinal but ranked as continuous variables, coded "1" highest to "6" lowest).
RQ2c	Binomial logistic regression statistics test the significance of the association between the monthly number of prescribed medications (IV) and odds of Obtaining free samples from doctors or patient assistance programs (DV), controlling for demographics (Race, Age, Gender) and socioeconomic (Income, Education) variables.	DV, participants' responses to survey question 12 four items checklist, (Obtained free samples from doctors or patient assistance programs) "Used" coded "1" or "Not Used" coded "2" over the last 12 months. IV, the respondent's response to questions (8) monthly number of prescribed medications (6 item scale ratio, measured as ordinal but ranked as continuous variables, coded "1" highest to "6" lowest).
RQ2d	Binomial logistic regression statistics test the significance of the association between the monthly number of prescribed medications (IV) and odds of Splitting pills or changing dosage frequency (DV), controlling for demographics (Race, Age, Gender) and socioeconomic (Income, Education) variables.	DV, participants' responses to survey question 12 four items checklist, (Split pills or change dosage frequency) "Used" coded "1" or "Not Used" coded "2" over the last 12 months. IV, the respondent's response to questions (8) monthly number of prescribed medications (6 item scale ratio, measured as ordinal but ranked as continuous variables, coded "1" highest to "6" lowest).
RQ3a	Binomial logistic regression statistics test the significance of the association between the health insurance status (IV) and odds of Purchasing medication over the internet (DV), controlling for demographics (Race, Age, Gender) and socioeconomic (Income, Education) variables.	DV, participants' responses to survey question 12 four items checklist, (Purchase medication over the internet) "Used" coded "1" or "Not Used" coded "2" over the last 12 months. IV, the respondent's response to survey questions (9) on health insurance status (Two categories: Yes and No, "Yes" coded "1" and "No" coded "2")
RQ3b	Binomial logistic regression statistics test the significance of the association between the health insurance status (IV) and odds of Purchasing medications from other countries	DV, participants' responses to survey question 12 four items checklist, (Purchase medication from other countries) "Used" coded "1" or "Not Used" coded "2" over the last 12 months. IV, the

	(DV), controlling for demographics (Race, Age, Gender) and socioeconomic (Income, Education) variables.	respondent's response to survey questions (9) on health insurance status (Two categories: Yes and No, "Yes" coded "1" and "No" coded "2")
RQ3c	Binomial logistic regression statistics test the significance of the association between the health insurance status (IV) and odds of Obtaining free samples from doctors or patient assistance programs (DV), controlling for demographics (Race, Age, Gender) and socioeconomic (Income, Education) variables.	DV, participants' responses to survey question 12 four items checklist, (Obtained free samples from doctors or patient assistance programs) "Used" coded "1" or "Not Used" coded "2" over the last 12 months. IV, the respondent's response to survey questions (9) on health insurance status (Two categories: Yes and No, "Yes" coded "1" and "No" coded "2")
RQ3d	Binomial logistic regression statistics test the significance of the association between the health insurance status (IV) and odds of Splitting pills or changing dosage frequency (DV), controlling for demographics (Race, Age, Gender) and socioeconomic (Income, Education) variables.	DV, participants' responses to survey question 12 four items checklist, (Split pills or change the dosage frequency) "Used" coded "1" or "Not Used" coded "2" over the last 12 months. IV, the respondent's response to survey questions (9) on health insurance status (Two categories: Yes and No, "Yes" coded "1" and "No" coded "2")
RQ4a	Multiple regression statistics test to predict the significance and the likelihood (odds) of the dependent variable (DV - Purchase medication over the internet, question 13 (1) composite score) from the multiple independent variables- IVs (insurance status, monthly out-of-pocket OOP expenses, the monthly number of prescribed medication) while controlling for demographics (Race, Age, Gender) and socioeconomic (Income, Education) - (Co-variables).	DV, participants' responses to survey question 13, four items (1) composite score, (Purchase medication over the internet) measured at a continuous level (composite Likert five scale score coded "1-extremely unlikely to "5-extremely likely"). IV, the respondent's response to questions (11) on OOP expenses(5 item scale ratio, measured as ordinal (in U.S. dollars) but ranked as continuous variables, coded "1" highest to "5" lowest); the respondent's response to survey questions (8) the monthly number of prescribed medications (6 item scale ratio, measured as ordinal but ranked as continuous variables, coded "1" highest to "6" lowest); the respondent's response to survey questions (9) on health insurance status (Two categories: Yes and No, "Yes" coded "1" and "No" coded "2"). CV, controlling factors participants response to Survey questions (1-5) - demographics (Race, two categories: "White" coded "1" and "Black or African American" coded "2"), Age, measured in years), Gender, two categories: "Male" coded "1" and "female" coded "2"), and socioeconomic (Income, measured in U.S. dollars and education, measured on a scale ratio 1 to 5) are continuous scale levels Coded highest "1" to Lowest "5").
RQ4b	Multiple regression statistics test to predict the significance and the likelihood (odds) of the dependent variable (DV - Purchase of medication from other countries, question 13 (2) composite score) from the multiple independent variables- IVs (insurance status, monthly OOP expenses, the monthly number of prescribed medication) while controlling for demographics (Race, Age, Gender) and socioeconomic (Income, Education) - (Co-variables).	DV, participants' responses to survey question 13, four items (2) composite score, (Purchase of medication from other countries) measured at a continuous level (composite Likert five scale score coded "1-extremely unlikely to "5-extremely likely"). IV, the respondent's response to questions (11) on OOP expenses(5 item scale ratio, measured as ordinal (in U.S. dollars) but ranked as continuous variables, coded "1" highest to "5" lowest); the respondent's response to survey questions (8) the monthly number of prescribed

		medications (6 item scale ratio, measured as ordinal but ranked as continuous variables, coded "1" highest to "6" lowest); the respondent's response to survey questions (9) on health insurance status (Two categories: Yes and No, "Yes" coded "1" and "No" coded "2").
RQ4c	Multiple regression statistics test to predict the significance and the likelihood (odds) of the dependent variable (DV - Obtained free samples from doctors or patient assistance programs, question 13 (3) composite score) from the multiple independent variables- IVs (insurance status, monthly OOP expenses, the monthly number of prescribed medication) while controlling for demographics (Race, Age, Gender) and socioeconomic (Income, Education) - (Co-variables).	DV, participants' responses to survey question 13, four items (3) composite score, (Obtained free samples from doctors or patient assistance programs) measured at a continuous level (composite Likert five scale score coded "1-extremely unlikely to "5-extremely likely"). IV, the respondent's response to questions (11) on OOP expenses(5 item scale ratio, measured as ordinal (in U.S. dollars) but ranked as continuous variables, coded "1" highest to "5" lowest); the respondent's response to survey questions (8) the monthly number of prescribed medications (6 item scale ratio, measured as ordinal but ranked as continuous variables, coded "1" highest to "6" lowest); the respondent's response to survey questions (9) on health insurance status (Two categories: Yes and No, "Yes" coded "1" and "No" coded "2").
RQ4d	Multiple regression statistics test to predict the significance and the likelihood (odds) of the dependent variable (DV - Split pills or change the dosage frequency, question 13 (4) composite score) from the multiple independent variables- IVs (insurance status, monthly OOP expenses, the monthly number of prescribed medication) while controlling for demographics (Race, Age, Gender) and socioeconomic (Income, Education) - (Co-variables).	DV, participants' responses to survey question 13, four items (4) composite score, (Split pills or change the dosage frequency) measured at a continuous level (composite Likert five scale score coded "1-extremely unlikely to "5-extremely likely"). IV, the respondent's response to questions (11) on OOP expenses(5 item scale ratio, measured as ordinal (in U.S. dollars) but ranked as continuous variables, coded "1" highest to "5" lowest); the respondent's response to survey questions (8) the monthly number of prescribed medications (6 item scale ratio, measured as ordinal but ranked as continuous variables, coded "1" highest to "6" lowest); the respondent's response to survey questions (9) on health insurance status (Two categories: Yes and No, "Yes" coded "1" and "No" coded "2").

After considering other statistical significance tests, the logistic regression statistics test applies to this study (Table 1 above). I begin my analysis with the binomial logistics regression model to answer RQ1a-3d. The following assumptions are identified in the study design and research questions (RQ1a-3d) as met, necessitating the binomial logistic regression statistical analysis (Laerd Statistics, 2017).

Assumptions: (1) The study's dependent variables are measured separately on a dichotomous scale. Split pills or change dosage frequency (Two Group "Used" or "Not Used"), Purchase medication over the internet (Two Group "Used" or "Not Used"), Purchase medication from other countries (Two Group "Used" or "Not Used"), Obtain free samples from doctors or patient assistance programs (Two Group "Used" or "Not Used").

(2). The study's independent and co-variate variables are measured on either a continuous (an interval or ratio scale variable) or nominal scale variables.

(3). There is an Independence of observations between each category of the dependent variable and the observations in each category of the study's nominal independent variables. In other words, there is no relationship between the categories. In this study, to predict whether T2D patients prescribed any medication "Used or Not Used" (Two categories or group), alternative medication cost-savings strategy (dichotomous DV) are based on the individual participant's responses to the study survey questions measured as ordinal but ranked as continuous independent variables (IV): monthly OOP expenses (measured in U.S. dollars), the monthly number of prescribed medications (Measured in term of the number of medication), and the nominal independent variable of health insurance status (Two categories: Yes and No) while the question on the Type of insurance (Seven categories: Medicaid, Veteran's benefits, Employer Insurance, Union or Retire health coverage, Medicare prescription plan, Affordable Care Act (ACA) or Medicaid Expansion, Other private insurance/not sure) are not included in the analysis but coded for descriptive statistics purpose. All the categories are mutually exclusive and exhaustive (Laerd Statistics, 2017).

(4). The study estimated more than 15 cases bare minimum per independent variable (385 cases in this study) needed for Binomial logistic regression that relies on maximum likelihood estimation and ensures the reliability of estimates not to decline significantly for combinations of cases when there are few cases (Laerd statistics, 2017).

(5). Assumption of linearity – The logistic regression model must be correctly specified (Laerd statistics, 2017). The assumption expressed as "linearity in the logit" is the same in the dependent variable's multiple regression log-odds transformations (logit). However, to answer this study's research questions (RQ1a – 3d), log-odds (transformation) were performed, it is of the dependent variable itself (Hilbe, 2016; Laerd statistics, 2017). According to Laerd statistics (2017), for a unit increase in the continuous independent variable, the value of the log odds (logit) of the dependent variable increases by a constant amount to assume linearity. For example, in this analysis, for every increase in one unit measure of continuous independent variables (e.g., age, scale-ratio,18-24 years to 25-34 years), the log odds (logit) of the dependent variable (e.g., Purchase from the internet) also increase by a constant amount. The constant is expressed as the slope coefficients' value, and it differs for each continuous variable in the analysis.

The assumptions of linearity were tested, assessed, or taken to relate to how the data fits the binomial logistics regression model. When violated, to further test or assess the linearity in the logits of dependent variables in this study analysis, I performed the Box-Tidwell procedure (Box & Tidwell, 1962), appropriate for the logistic regression model (Fox, 2016) using the SPSS 27.0 statistics software. Noting that when any continuous independent variables are linearly related to the dependent variables' logit, the Box-Tidwell procedure has two concerns. The procedure may be insensitive to a small departure from linearity. It may not detect nonlinearity's type (shape) when the relationship linearity is small (Hosmer & Lemeshow, 1989; Laerd statistics, 2017). I used the procedure's result to estimate an appropriate transformation to correct some nonlinearity (Menard, 2010). The transformation also corrects other assumptions of binomial logistic regression (Laerd Statistics, 2017).

Using SPSS statistic software, I transformed the continuous variable that violated the assumptions and checked whether the transformed continuous independent variable (s) is linearized to the dependent variable's logit, and interpreted the SPSS statistic software result of Box-Tidwell using the variables in the equation table generated containing the interaction terms and examine the value in the "sig," that is, the significance row of the table. After inspection, when the interaction is statistically significant, the original continuous independent variable is not linearly related to the dependent variable, i.e., indicating that it failed the linearity assumption.

To account for multiple statistical tests (multiple comparisons), I used SPSS 27.0 statistics software analysis. Bonferroni Correction was recommended based on the model's terms (Tabachnick & Fidell, 2014). For analyses, the research questions in this study have variable terms accounting for all variables in the analysis model that included the five interaction terms of the Box-Tidwell procedure and one (1) intercept called constant in the SPSS statistics. The Bonferroni correction using the terms (e.g., 14) in the model and the power of the study sample size analysis, i.e., original *p*-value (0.05), the new *p*-value at which statistical significance would be accepted is .05 divided by the number of terms (14) = $P \leq 0.00357$. Confidence interval (CI) 95% for odd ratio. The Bonferroni corrected (adjusted) alpha (α) level – $P \leq 0.00357$ was applied in the analysis for all continuous independent variables to be linearly related to the odd log (logit) of the dependent variable for the applied research questions.

The assumption of an outlier in logistic regression analysis was tested, and I corrected or removed using the case-wise diagnostic option in the SPSS 27.0 software analysis. The study's potential covariables were also included in the model term to correctly answer the research question and determine their influence on the association between the study variable of interest.

Interpreting the Results (Binomial logistic regression; RQ1a- 3d): Using tables generated by the SPSS 27.0 statistics software, I first inspect the "case processing summary" table to determine if any missing cases (385 sample size is required for this study). Check the "Dependent variable Encoding" table for the correct coding ("yes" coded "Used" or "No" coded "Not Used") "categorical independent variables" to determine if any category is undercounting and properly coded. Check the “Classification Table,” “Variables in the Equation,” and “Variables not in the Equation” tables; this confirms which variables are added to the model. To determine the overall statistical significance of the binomial logistic regression model. I first determine how well the model is not fit using the Hosmer and Lemeshow goodness of fit test, which indicates the model is significantly fit to predict categorical outcomes (Laerd Statistics, 2017). Then apply Nagelkerke R Square values to understand how much variation in the dependent variable is also referred to as *pseudo* R^2 values in the model. Based on the observed and predicted classification, SPSS statistics set the cut value as .500, which is the probability of a case (participant response to independent variables) being categorized or classified into “Used,” if less than .500, the case is classified as "Not Used" category.

Analysis continues; based on a cut value of 0.5, the SPSS statistics generated the following measures that assess the ability of a binomial logistic regression model to classify cases correctly:

percentage accuracy in classification (PAC) – overall % with the independent variables’ addition to the classification reflected in the table.

Sensitivity - % of the case that has the observed characteristics.

Specificity - % of the case that did not have the observed characteristics.

Positive predictive value - % of correctly predicted cases compared to the total number of cases predicted as having the characteristic. E.g., 385 x (Used ÷ (Not Used + Used)

Negative predictive value - % of correctly predicted cases without observed characteristics than the number of cases predicted as not having characteristics. E.g., 385 x (Not Used ÷ (Not Used + Used).

The Receiver Operating Characteristic (ROC) Curve – is a measure of the binomial logistic regression model's overall discriminatory ability. The curve is
a plot of sensitivity versus one minus specificity (Hilbe, 2016). The ROC does not depend on one cut value but considers all possible cut-off points in the data and how each cut-off point changes the test's specificity and sensitivity. The ROC curve was produced in SPSS Statistics using the ROC Curve procedure.
The Wald test was used to determine statistical significance for each independent variable. SPSS Statistics also includes the odds ratios of each of the independent variables in the "Exp(B)" column along with their confidence intervals "(95% C.I. for EXP(B)" column; Laerd Statistics, 2017).

I continue the statistical analyses with the multiple regression statistical test to test the significance or hypotheses of this study RQ4a-d. I used the participant's response to the survey question 13 to measure intention to use the cost-savings strategy (DV) based on four items composite scale scores. According to Laerd statistics (2015), the following two assumptions are identified in the study design, research questions, and theoretical ground (1). The individual dependent variable is measured at a continuous level (i.e., composite scale score from 1 to 5). Split pills or change dosage frequency ("1 = Extremely Unlikely" "2 = Unlikely," "3 = Neutral," "4 = likely," and "5 = Extremely likely"), Purchase medication over the internet ("1 = Extremely Unlikely" "2 =

Unlikely," "3 = Neutral," "4 = likely," and "5 = Extremely likely"), Purchase medication from other countries ("1 = Extremely Unlikely" "2 = Unlikely," "3 = Neutral," "4 = likely," and "5 = Extremely likely"), Obtain free samples from doctors or patient assistance programs ("1 = Extremely Unlikely" "2 = Unlikely," "3 = Neutral," "4 = likely," and "5 = Extremely likely").

(2). The analysis has two or more independent variables: either continuous (i.e., an interval or ratio variable) or categorical (i.e., an ordinal or nominal variable).

However, I tested and assessed the following multiple regression assumptions for a violation to ensure the data fits the multiple regression model: (a) Assumption of independence of observation: the Durbin-Watson test was performed to test for independence of residual (error) used to detect possible autocorrelation in SPSS statistics.

(b) Assumption of a linear relationship between the predictor variables (and composite) and the dependent variable: I tested (1) – that a linear relationship exists between the dependent and independent variables collectively – by plotting a scatterplot of the studentized residuals against the (unstandardized) predicted values. (2) A linear relationship exists between the dependent and independent variables – using partial regression plots between each independent and dependent variable. If the relationship between one or more independent variables and the dependent variable does not follow a straight line, the data has failed the assumption of linearity. A transformation may be applied to the independent, dependent, or both, if any (none in this situation). I will perform the Box-Tidwell procedure (Box & Tidwell, 1962) as explained in the binomial logistic regression above or the Box-Cox method (1964) to find the correct transformation (Box & Cox, 1964).

(c) Assumption of homoscedasticity of residuals (equal error variances): Homoscedasticity assumes that the variance is equal for all predicted dependent variable values. To check for heteroscedasticity, I used the plot created to check linearity in the SPSS statistics plotting the studentized residuals (SRE_1) against the unstandardized predicted values (Laerd, 2015). However, suppose the residuals (errors) are not evenly spread but differ in height (e.g., a funnel shape). In that case, instead of heteroscedasticity, the assumption of homogeneity of variance failed. I took one of these remedial action, according to Laerd statistics (2015): (1) run a weighted least squares regression equation; (2) run a regression with robust standard errors; (3) run a robust regression; or (4) transformation of the dependent variable (and possibly independent variable(s) as well).

(d) Assumption of no multicollinearity: Multicollinearity occurs when two or more independent variables are highly correlated, hindering understanding which variable contributes to the variance explained by technical issues in calculating a multiple regression model (Laerd, 2015). To test for multicollinearity, I inspected the correlation coefficient (for descriptive in the linear regression) to check that none of the independent variables have correlations greater than 0.7. I consulted the “Tolerance” and “VIF” values in the Coefficients table generated in SPSS statistics (Laerd, 2015). If the Tolerance value is less than 0.1, a VIF of greater than 10 - the collinearity assumption have failed (Hair et al., 2014). The selection was made on theoretical grounds and reran the multiple regression procedure to recheck the assumptions.

(e) Assumption of no significant outliers, high leverage points, or highly influential points: The casewise diagnostic options were inspected in SPSS statistics to check outliers. I checked the data to see if there is an outlier (greater than ±3 standard deviations). It may be a data entry error or a particular independent variable value in understanding why the prediction was so far from the observed value (Laerd, 2015). I further determined whether any cases have problematic leverage values in the linear regression. Leverage values less than 0.2 as safe, 0.2 to less than 0.5 as risky, and values of 0.5 and above may be dangerous (Huber, 1981). I then select for cooks option in linear regression (SPSS statistics dialog box) to check for influential points. If any values for Cook's Distance are of concern, I will transform or remove them to resolve the issue.

(f) Assumption of normality of the residuals (errors): means the errors (residuals) should be approximately normally distributed. To run inferential statistics (i.e., determine statistical significance), the prediction errors (or the residuals) need to be normally distributed. To check for the assumption, I visually assessed: (1) a histogram with a superimposed normal curve and a P-P Plot, which were both produced by the options selected in the earlier Linear Regression (SPSS statistics): Plots dialogue box (use *standardized residuals*); or (2) a Normal Q-Q Plot of the *studentized residuals* (Laerd, 2015). Suppose the assumption of normality is markedly violated. In that case, I either run a regression analysis, which does not rely on normally distributed errors, or perform a Transformation on the dependent variable or independent variables to coax the error residuals to normality (Laerd, 2015).

Interpretation of Result (Multiple regression analysis; RQ4a-d): I first examined the variables entered into the multiple regression model to confirm that the independent variables were entered correctly and the method used, indicating "entered." These referred to the regression "Model 1" to reference the model tables in the SPSS statistics (Laerd, 2015). I used any of the following measures to determine whether the multiple regression model is a good fit for the data:

(a) the multiple correlation coefficient (R) values are found in the "R" column of the Model Summary table. For example, *R* is the Pearson correlation coefficient between the scores predicted by the regression model (i.e., the predicted scores, PRE_1) and the dependent variable's actual values (i.e., Purchase from internet scores). According to Laerd (2015) SPSS statistics, a multiple correlation coefficient of 0 (zero) indicates no linear association between the dependent and independent variables, and a value of 1 is a perfect linear association.

(b) the percentage (or proportion) of variance explained (R^2 and adjusted R^2): The value of R^2 is presented in the "R Square" column in the analysis Model Summary table. The dependent variable's proportion of variance is explained by the independent variables over and above the mean model. According to Laerd (2015), R^2 is based on the sample and is considered a positively biased estimate of the proportion of the dependent variable's variance accounted for by the regression model (i.e., it is larger than when generalizing to a larger population). R^2 is considered a good starting measure for understanding the results (Draper & Smith, 1998). Also, the adjusted R^2 value found in the "Adjusted R Square" column of the Model Summary table corrects the positive bias to provide a value expected in the population. In a normal fit, Adjusted R^2 will always be smaller than R^2. According to Cohen's (1988) classification, Adjusted R^2 is also an estimate of effect size, which at 0.559 (55.9%), it indicates a large effect size (Cohen, 1988).

(c) Examine the statistical significance of the overall model: Using SPSS statistics, the statistical significance of the overall model (i.e., the model containing all independent variables) is presented in the "Sig." column of the ANOVA table in the SPSS statistics (Laerd Statistics, 2015). If the "Sig." value is .000, $p < .0005$. If $p < .05$, the result is statistically significant. However, if $p > .05$, the result is not statistically significant. This outcome means that the addition of all independent variables and covariables (i.e., the overall model) are statistically significant to the dependent variable and fit the data more than the mean model (Laerd, 2015).

Interpretation of the Coefficients: To ascertain the coefficients' value, I inspected the SPSS statistics Coefficients table generated in the analysis. The intercept is called the constant in SPSS Statistics. The value of the intercept is found in the "(Constant)" column under the "B" column. The intercept is not usually of much interest. It is the value of the dependent variable when all the independent variables are zero. The intercept is usually statistically significant (i.e., $p < .0005$), meaning that it is different from 0 (zero) has no "real world" meaning, and I did not consider it in any more detail. Again, this is of little interest. More importantly and of much greater interest are the slope coefficients, which I considered.

Interpreting the Continuous Independent Variable - I interpreted the continuous independent variables' slope coefficients. For the continuous independent variables, the slope coefficient represents the change in the dependent variable for a one-unit change in the independent variable.

Interpretation of the Dichotomous Independent Variables:

A dichotomous independent variable, such as gender, has a different interpretation than continuous independent variables. In the dichotomous independent variable situation, the slope coefficient's value represents the dependent variable between the two categories of the dichotomous independent variable. I evaluated the 95% confidence interval (CI) and statistical significance of this difference in the same way I did for the continuous independent variables.

Predicting the Dependent Variable: Predictions and confidence intervals (95% confidence interval mean prediction based on sample size for the study) were made, resulting in the SPSS Statistics analysis report for each model analyzed.

Threats to Validity

Threats to External Validity

The study sample only includes adult diabetic patients that use prescription medication. However, oversample those with or without insurance, which may affect the generalizability of the population. Also, the population size of the 385 survey respondents may not represent the entire adult T2D population in the U.S. that used the strategies. In addition, a period is given for participants to respond. The nature of the survey's administration (Amazon Turk) may also pressure the individual to answer without giving much thought to the survey questions, especially when reporting the variables needed for the study objective, which will likely affect the external validity (Adepoju et al., 2019). However, to ensure external validity, the Cronbach's alpha procedure on SPSS statistics was used to measure the survey response bias for internal consistency (reliability) in a questionnaire that measures a set of variables on a scale. The utility of this approach to assess survey selection bias and reliability was reported in Jian et al. (2016) and Karimy et al. (2019).

Threats to Internal Validity

This study's internal validity threat is that participants' responses to the cost-savings strategies question or survey queries may not reflect the strategies' action. For example, splitting pills may have been used to fulfill medication dosage and not determined to make medication last longer. Also, participants may obtain a prescription from physicians to try a new drug. Suggesting issues unrelated to the cost-related access barrier have been investigated (Musich et al., 2015). Because of untrackable claim sources of the cost-saving strategies considered in this study, data are not compared to those medications' actual pharmacy claims or insurance coverage. However, this study does not aim to evaluate OOP expenses' actual cost but as a predictor of utilization of the cost-savings methods that negatively impact medication noncompliance. Thus, the internal validity threat might be a cross-sectional self-reported survey design from the research design. Identifying the statistics and statistical computer programs for testing the hypothesis-related variables drawn from the sample to the study population required assumptions. The Cronbach's alpha procedure on SPSS statistics was used to measure the survey response internal consistency (reliability) in a construct reflecting different underlying factors that employed the questionnaire. At the same time, binomial multiple logistic regression statistical tests (assumptions) answer the research questions relating three independent variables and a continuous dependent variable that yields the study's expected relationship (Creswell, 2014; Lund Research, 2018).

Ethical Procedures

Agreements to gain access to participants or data (include actual documents in the IRB application, appendix A): Approval to conduct the study (IRB Number is 07-29-21-0619178) was granted by Walden University on July 28, 2021. The invitation letter was distributed and became active on July 29, 2021, and paused on August 08, 2021, via Amazon Mechanical Turk Crowdsourcing Marketplace (AMTCM) to the mTurk members (http://www.mturk.com) online with a link to the online study questionnaire designed in the Qualtrics platform captured the CAHPS Survey (CAHPS –ACOs- Survey 2018 CAHPS® Survey for Accountable Care Organizations (ACOs) participating in Medicare Initiatives) used to query patients and consumers to report on and evaluate their experiences and satisfaction with Medicare delivery systems. Participants answered background questions (Demographic/ socioeconomic directly from the CAHPS survey) and CAHPS modified or standardized questions relevant to this study. E.g., questions about cost-savings strategies and insurance status (Musich et al., 2015).

Ethical concerns related to recruitment and a plan to address them: participation in the research survey is considered optional: members or workers who received the invitation can take their time to decide about participation within the frame at which the survey is open. Certain vulnerable adult populations may unknowingly participate, given the research topic and overly invasive screening. Thus, the sampling strategy included an eligibility criterion for adults (18+ yrs.) who self-reported being diagnosed with diabetes and prescribed any medication for their diabetes condition. Those who did not answer the survey questions on cost savings or not taking prescription medication in the last twelve months were not counted. The researcher is a student with sufficient research coursework and training. The participants first received an invitation that detailed information about the study online (through AMTCM). If interested in participation, they will click on the anonymous link and be directed to the (Qualtrics) survey platform and complete an informed consent form to start the survey. Informed consent provides information about the study with enough time to review it before accepting or declining to participate in the study. Clicking a mouse to consent automatically document or save the response.

Ethical concerns related to data collection and a plan to address them: The language used in the informed consent form is understandable to the participants. The consent form explains the sample inclusion criteria (e.g., age above 18 years or older adult and U.S. resident diagnosed with diabetes and prescribed any medication) to understand why they participate. The consent form explicitly explained the purpose of the research and included instructions on data collection procedures. It is bright and stated in the consent form that participation is voluntary. It also gives participants the right to decline or discontinue the survey at any time for any reason with no penalty. In addition, the consent form indicated no possible harm beyond the risk of daily life (if any minimal potential threat), and participants are not required to waive any legal rights. The consent form includes the information that participants may not benefit directly, but the society. The compensation (stipends or reimbursement) for completing the survey is (e.g., $1.00). The consent form described that participants' privacy is automatically protected, explaining the code or identifier, which does not permit the researcher to use their name or contact info in reporting. The data obtained will only be used for research. The consent form indicated the researcher's potential conflict of interest disclosure. The consent document protects participants' legal rights and does not require participants to waive any legal rights. The consent form included the researcher's (student) name and email address and the Walden University research participant's advocate number for contact or questions.

Protection for confidential data: Confidential data is protected as the survey is self-reported and anonymous. The participant's contact and name are not recorded or disclosed in the report. The data were stored electronically, and password protected in the researcher's computer backed up on a password-protected hard drive. The informed consent was separated from other materials and stored for at least five years, after which they would be destroyed along with the data. The survey is anonymous; the verification code is generated randomly by clicking on a link to ensure a survey returns and completion. In other words, to ensure anonymity for participants and data collection purposes – once the participants accept the invitation, the survey software generates a numerical Code by clicking on the survey link to participate.

Although the response is self-reported and cross-sectional, the participants' demographic information or descriptor is a combination of details that will not indirectly or intentionally identify any individual. The researcher and Walden faculty (supervisor) have access to the results. The potential risk of participating in the study is minimal (not more than those encountered in regular daily life). Already acknowledged and described in the invitation and consent in the Qualtrics platform, the probability and magnitude of harm or discomfort anticipated in the research are not greater in and of themselves than those ordinarily encountered in daily life or during the performance of routine physical or psychological examinations or tests. The researcher is a student and has no conflict of interest or dual role in the study's contest.

The research risk and burden are considered reasonable to the participants to effectively address the literature gap and health service practice. Participant recruitment was coordinated in a non-coercive manner because most (mTurk members) do this in their free time. AMTCM (organization) invites members or workers who meet the inclusion or qualification criteria. However, the platform allows participants to opt-out without retaliation or association with their membership standing, and members can only opt-in when they meet the inclusion criteria. The incentive or stipends ($1.00) are token compared to what members usually get paid.

Summary and Transition

This quantitative study is a cross-sectional survey design derived from primary data. The survey was captured in CAHPS, 2018, designed in the Qualtrics platform, and administered online through the Amazon Mechanical Turk crowdsourcing marketplace. The design and distribution technique enables the researcher to maximize the target population (Adepoju et al., 2019). Understanding how OOP expenses, number of prescribed medications, and insurance status predict the use of alternative cost-saving strategies to source low-cost prescription medication is significant. The study includes adult T2D patients, ages 18+, who are more likely to use more medications and have comorbid conditions or disabilities. The study's objective is to investigate the predictors of using an untrackable alternative source of drugs to reduce prescription medication costs in T2D, controlling patients' socioeconomic and demographics.

I use a quantitative research paradigm guided by the theory of reasoned action (TRA) using a multiple binomial logistic regression model to examine the association between participants' utilization of each alternative cost-saving strategy (DV) to obtain low-cost medications and self-reported monthly OOP expenses, the monthly number of prescribed medications, and insurance status (IV) in T2D controlling for patients socioeconomic and demographics. The cost-saving strategies (DV) include the use of the following: obtaining free samples from physicians or patient assistance programs, splitting pills or changing dosage frequency, purchasing medications from other countries, and purchasing over the internet (Musich et al., 2015). The patients' self-reported characteristics- e.g., demographic, and socioeconomic status- are the controlled variable influencing the outcome.

The study is a cross-sectional, patients' self-reported survey designed in the Qualtrics platform and administered online. The questionnaire instrument included a validated Consumer Assessment of Healthcare Providers and Systems (CAHPS) survey that was funded and overseen by the U.S. Agency for Healthcare Research and Quality (AHRQ). The survey is designed to query patients and consumers to report on and evaluate their experiences and satisfaction with Medicare delivery systems (CAHPS, 2018; Musich et al., 2015). The survey will be used in this study as follow:

Part I (CAHPS survey)- (Part I) measure respondents' demographics (e.g., sex, race, gender), socioeconomic factors (income, education) characteristics used to identify respondent's health needs, satisfaction, and experience with intervention or other components of health care services (CAHPS, 2018). The second section (Part2), modified (CAHPS survey) to measure patients' self-reported utilization of alternative cost-saving strategies (untrackable) sources on prescription medication and insurance status reported by Musich et al. (2015), included monthly prescription drug OOP expenses and the monthly number of prescribed medication questions applicable to this studies objective. Respondents are adults 18 or older, diabetic with self-reported medication prescription usage at the study baseline to the end of the study. Multivariate logistic regression statistics test determined the significance of independent variables (predictors) associated with alternative cost savings strategies controlling for demographics in T2D adults.

This chapter provides insight into the methodology, design, and data analysis plan, including the statistical model that answers the study research questions. The ethical study procedures and external and internal validity threats are also discussed. The next chapter (4) of this study reports the results and changes in the data collection procedure or statistics used to analyze the result.

Chapter 4: Results

Introduction

The purpose of this study is to examine whether insurance status, OOP expenses and the number of prescribed medications may be predictors for the use of alternative cost-saving strategies by adults diagnosed with T2D. The research questions investigated if there is an association between the participant's self-reported monthly number of prescribed medication, monthly OOP expenses, health insurance status, and multiple alternative cost-saving strategies (purchasing medication over the internet; purchasing medication from other countries; obtaining a free sample from doctors or patients' assistance programs; splitting pills or changing dosage frequency) used and likely to use in the past 12 months while controlling for demographics (race, age, gender) and socioeconomic (income, education) factors. The hypotheses test the significance of the association between the independent variables and each alternative cost-saving strategy dependent variable. In the next sections of this chapter, I will discuss the data collection procedure, data cleaning, and discrepancies in methodology from Chapter 3. In the result section, I first present the population sample's baseline descriptive statistics related to the characteristics of the participants of each variable and then provide the statistical assumptions and analysis that answered the study research questions. I concluded the chapter with a summary.

Data Collection

The data collection used an online survey instrument designed in the Qualtrics platform. It is administered online with a link distributed through the Amazon Mechanical Turk Crowdsourcing Marketplace (AMTCM) to the mTurk members (http://www.mturk.com); mTurk members are notified about the research study purpose, eligibility criteria, and compensation before accepting to participate whereby they are directed to the Qualtrics platform to complete the 13 questions in the survey, which was published live and became active on July 29, 2021. Over 400 responses were received in the first week. Overall, 421 participants and 400 responses were accepted (paid) as completed, and 21 were rejected via mTurk as started but not completed. The survey was paused on August 08, 2021, when the actual response of 400 participants requested via mTurk that completed the survey was accepted. Participant responses were accepted if they met the eligibility criteria based on their responses to survey questions about being diagnosed with diabetes (Q6) and using any prescribed medication in the last 12 months (Q7) of the survey questionnaire (Appendix A). A total of 385 responses met the study eligibility criteria, including location in the United States reported in the tracked mTurk members location GPS, age 18 years above, and most importantly, self-reported having been diagnosed with T2D and being prescribed medication for T2D condition in the last 12 months.

Data Cleaning

Overall, all the 385 participants that met the eligibility criteria and expected sample size for the study were included in the data set. After inspection for missing data in response to the 13 survey questions, I determined that the missing data on variables to be evaluated are negligible compared to the number of cases selected for each variable, so all responses were included in the data set for analysis. It was also noted that the survey response categorizes race and ethnicity, that is, survey question (Q4) that included three options White, Black or African American, and Latino ethnic background. However, only two categories (White and Black or African American) are needed in the analysis. I determine that seven out of the 379 responses excluding missing responses to the question (Q4) in this category are negligible considering that the missingness is independent of all other variables and removal. So, other responses, in this case, were included in the data set and analyzed.

Data Collection Discrepancies

Propensity weighting was proposed to adjust survey selection bias in the plan presented in Chapter 3. The propensity weighting utilizes demographic and socioeconomic variables that could influence survey response bias. However, it was found that previous researchers reported that demographic and socioeconomic factors influence the utilization of the dependent variables investigated in this study (Cha & Cohen, 2019; Hong et al., 2020; Musich et al., 2015). This study controls these factors, and the research design is not observational or randomized control. It was determined later that the value of the variable of interest in a binomial and multiple logistics regression model that measures the outcome was independent of those factors or covariables (demographic and socioeconomic) in the sampling (Solon et al., 2015). So, multiple regression propensity weighting might not be necessary.

Thus, I used the Cronbach procedure to test the reliability of the survey questionnaire response to measure the internal consistency of a set of variables in a scale, i.e., the four separate dependent variables measured in this study (participants' "intention" to use cost-saving strategy for study theoretical perspective). Since one construct in the study used a self-designed self-reported question, reflecting different underlying factors that employed the questionnaire (Survey Q13). I conducted a Cronbach's alpha procedure on SPSS statistics to measure internal consistency (reliability) on the questionnaire employed to measure the constructs on all 385 samples; the construct, "intention" to use cost-savings strategy, was employed for each dependent variable (Survey questionnaire Q13 (1-4), Appendix A) that used multiple regression model (analyze the association between multiple independent variables and one continuous dependent variable) to answer "likelihood of using strategy if participants cannot afford medication for diabetes condition." Therefore, (for DV, RQ4a—d), the response consisted of 5 points Likert scale ranging from "1-extremely unlikely" to "5-extremely likely." The Cronbach's alpha coefficient for the likelihood to use cost-savings strategy "intention" construct within the sample was 0.60. The utility of this approach to assess survey selection bias and reliability was reported in Jian et al. (2016) and Karimy et al. (2019).

Also, some changes in the operationalization of the data plan in Chapter 3. The race was coded “1” = White and “2” = Black or African American, and Latino ethnic group was removed from the analysis for better logistics regression results. None was also coded “6” in question (survey Q8) about the monthly numbers of prescription drugs. Participants' responses to the type of health insurance (survey Q10) were not coded as categorical variables in the analysis because the research questions that guided the scope of this study will only analyze health insurance status (survey Q9). However, the response was included in the survey descriptive statistics (characteristics of the sample) that illustrate future research recommendations section in Chapter 5.

Results

Demographic of Samples

The demographic and socioeconomic characteristics of the survey sample and missing data (if any) are shown in Table 2. For demographic characteristics, the total responses to the self-reported question on race, the majority were White (N = 264, 68.57%) compared to Black or African American (N = 108, 28.05%), and Latino ethnic background (N = 7, 1.82%). The majority of the participants self-reported income ranges in $51,000-75,999 (N = 210, 54.55%), and $25,000-50,999 (N = 111, 28.83%). The higher number of the participants were 4-year college graduates (N = 282, 73.25%). The average age of the participants was between 25 to 34 (N = 191, 49.61%) and 35 to 44 (N = 122, 31.69%) while most of the participants self -reported as male (N = 247, 64.16%) and female (N = 137, 35.58%).

Table 2

Descriptive Statistics for the Demographic (Age, Gender, Race) and Socioeconomics (Education, Income) Covariables in the Study Sample

Variables	Overall *N* = 385	
	%	*N*
Age		
18 to 24	4.7	18
25 to 34	49.6	191
35 to 44	31.7	122
45 to 54	9.6	37
55 to 64	4.2	16
65 to 69	0.3	1
70 and above	0.0	0
Gender		
Male	64.2	247
Female	35.6	137
Missing	0.3	1
Race		
White	68.6	264
Black or African American	28.1	108
Latino ethnic background	1.8	7
Missing	1.3	6
Educational level completed		
8th grade or less	0.0	0
Some high school, but did not graduate	0.5	2
High school graduate or GED	2.6	10
Some college or 2-year degree	7.5	29
4-year college graduate	73.3	282
More than 4-year college degree	15.8	61
Missing	0.3	1
Income level		
$76,000 – above	11.2	43
$51,000-75,999	54.6	210
$25,000-50,999	28.8	111
$24,000- below	5.5	21

As shown in Table 3 below, participants self-reported having been prescribed an average of 5 to 6 (N = 146, 37.9%) and 3 to 4 (N = 98, 25.5%) prescription medications in the last month for their diabetes condition. However, a higher number of the participants (N = 366, 95.1%) self-reported having health insurance, while some (N = 13, 3.4%) reported having no health insurance at all. Most participants self-reported monthly OOP expenses on prescription drug in the last 12 months that ranges between $115 -110 (N = 143, 37.1%), $116- 481(N = 129, 33.5%), $110 – 51 (N = 63, 16.4%), $50 – below (N = 27, 7.0%) or $481 and above (N = 22, 5.7%).

Table 3

Variable Descriptive - Participants Self-Reported Monthly Average Number of Prescribed Medications, Monthly OOP Expenses, and Health Insurance Status

RQ Associated	Variables	*%*	*N*
			Overall N = 385
1a,b,c,d and 4a,b,c,d (IV)	The number of prescribed medications for diabetes condition in the last month.		
	9 or more	1.3	5
	7 – 8	18.2	70
	5 – 6	37.9	146
	3 – 4	25.5	98
	1 – 2	14.8	57
	None	2.1	8
	Missing	0.3	1
3a,b,c,d and 4a,b,c,d (IV)	Health insurance status		

	Yes	95.06	366
	No	3.38	13
	Missing	1.56	6
2a,b,c,d and 4a,b,c,d (IV)	Monthly average out-of-pocket (OOP) expenses		
	$481- above	5.7	22
	$116 – 481	33.5	129
	$115 – 110	37.1	143
	$110 - 51.	16.4	63
	$50 - below.	7.0	27
	Missing	0.3	1

As seen in Table 4 below, participants also self-reported having one or more types of health insurance such as employer health insurance (N = 194, 38.6%), Medicaid (N = 131, 26.0%), Medicare prescription plan (N = 69, 13.7%), veteran benefit (N = 55, 10.9%), union or retired health coverage (N = 36, 7.2%), or Affordable Care act (ACA)/Medicaid expansion(N = 14, 2.8%).

Table 4

Frequency Table That Characterized the Participants' Self-Reported Type of Health Insurance Coverage

Type of health insurance	*Overall N = 503*	
	%	*N*
Medicaid	26.0	131
Veteran's benefits	10.9	55
Employer insurance	38.6	194
Union or retiree health coverage	7.2	36

Medicare prescription plan	13.7	69
Affordable Care Act (ACA) or Medicaid Expansion	2.8	14
Other private insurance/not sure	0.8	4

To further characterize the sample, participants self-reported using one or more cost-saving strategies to save money on prescription medication in the last 12 months (Table 5) and indicated intention on how likely they would use particular cost-savings strategy if they cannot afford all medication for diabetes condition (Table 6 below).

Table 5

Variable Descriptive - Participants Self-Reported Medication Cost-Saving Strategies Used in the Last 12 Months

RQ Associated	Cost-savings strategies used	Overall *N* = 511	
		%	*N*
1a, 2a, 3a (DV)	Purchase medication over the Internet	35.6	182
1b, 2b, 3b (DV)	Purchase medication from other countries	36.2	185
1c, 2c, 3c (DV)	Obtain free samples from doctors or patient assistance programs	20.7	106
1d, 2d, 3d (DV)	Split pills or changed the dosage frequency	7.4	38

Table 6

Variable Descriptive - Participants' Self-Reported Response to the Likelihood of Using a Medication Cost-Savings Strategy if all Medication Costs Cannot be Met

RQ Associated	Variable	Extremely unlikely	Somewhat unlikely	Neither likely nor unlikely	Somewhat likely	Extremely likely	Overall *N=385*
		%	*%*	*%*	*%*	*%*	*N=385*
4a (DV)	Purchase medication over	2.9	10.4	16.6	50.7	19.5	

	the internet					
4b (DV)	Purchase medication from other countries	3.4	10.1	23.9	33.8	28.8
4c (DV)	Obtain free samples from doctors or patient assistance program	1.3	3.6	19.2	48.6	27.3
4d (DV)	Split pills or change dosage frequency	2.3	6.2	15.3	41.0	35.1

To assess the theoretical perspective that guided this study, I calculated a summary descriptive statistics score (variables measured in the ordinal but ranked as continuous) for participants' self-reported responses to monthly OOP expenses (measured in U.S. dollars, corresponding to CMS (2017) prescription drug OOP claim, survey question 11) that measured attitude, and the monthly number of prescribed medications (measured in the number of prescribed medication, corresponding to the value with the Medicare prescription drug survey data CMS, 2017, survey question 8) that measured subjective norm in this study. I created a scale ratio measured in the ordinal based on five items. However, I ranked as continuous representing participants' attitudes in survey Question 11, which asked participants to indicate monthly average prescription drug OOP expenses for diabetes. The five items scale ratio were coded as follows: 1 = $481- above, 2 =$116 – 481, 3 = $115 – 110, 4 = $110 – 51, 5 = $50 – below, indicating "1" highest and "5" lowest. I also created six items scale ratio measured in the ordinal but ranked as continuous representing subjective norm. The survey question (8) asked participants to indicate how many medications, including those currently taking and any new medications, were prescribed for diabetes in the last month. The six items were coded as follows: “1” = 9 or more, “2” = 7 – 8, “3” = 5 – 6, “4” = 3 – 4, “5” = 1 – 2, “6” = none, indicating that score of “1” highest and “6” lowest subjective norm (societal perception) of intention towards using cost-savings strategy. I analyze the scale ratio score by averaging participants’ responses to the two independent variables of interest, monthly OOP expenses and the monthly number of prescribed medications. Participants’ responses on the monthly OOP expenses mean a score of 2.85 out of a possible 5 (SD = 0.996) for ATT. The monthly number of prescribed medications averages 3.41 out of a possible 6 (SD =1.05) for SNs. The score distribution is shown in Table 7. The Histogram Figure 2 and Figure 3 of the monthly OOP expenses and the Monthly number of prescribed medications show the variable to be normally distributed.

I also analyze the summary descriptive statistics score that measures intention, using participants’ responses to survey question 13 by asking what participants will do if participants cannot afford all medication for diabetes, given the option of scoring five items on the likelihood of using any of the four alternative strategies in the question. As shown in Table 8, on a scale of 1-5, score on 5 points Likert scale ranging from “1-extremely unlikely” to “5-extremely likely.” The mean score for DV, Purchase medication over the internet, 3.74 (SD 0.98) and 3.75 (SD 1.08) for DV, Purchasing medication from other countries. The average score for DV to obtain a free sample from Doctors or patient assistance programs was 3.97 (SD 0.85); and 4.0 (SD 0.98) for DV, split pills, or change dosage frequency.

Table 7

Descriptive Statistics Score for Participants' Monthly OOP Expenses (Attitude) and Monthly Number of Prescribed Medication (Subjective Norm) Variables

RQ Associated	Variables	Mean	Std. Deviation	Variance	Overall N= 384
RQ 4a, b, c, d (IV)	Monthly number of prescribed medication (SN)	3.41	1.05	1.11	
RQ 4a, b, c, d (IV)	Monthly average OOP expenses (ATT)	2.85	.996	.992	

Table 8

Descriptive Statistics Score of Participants' Intention or Likelihood to use Cost-Savings Strategy

RQ Associated	Intention to use variables	Minimum	Maximum	Mean	Std.Deviation	Variance	*Overall N= 385*
RQ4a (DV)	Purchase medication over the internet	1.00	5.00	3.74	0.98	0.96	
RQ4b (DV)	Purchase medication from other countries	1.00	5.00	3.75	1.08	1.17	
RQ 4c (DV)	Obtain free samples from doctors or patient assistance programs	1.00	5.00	3.97	0.85	0.73	
RQ 4d (DV)	Split pills or changed dosage frequency	1.00	5.00	4.00	0.98	0.96	

Figure 2

Histogram of the Participants' Self-Reported Monthly Number of Prescribed Medication

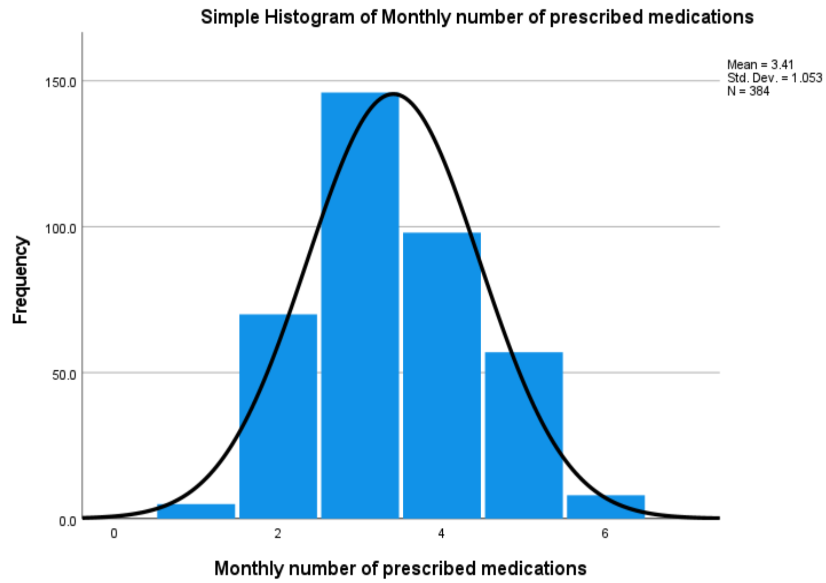
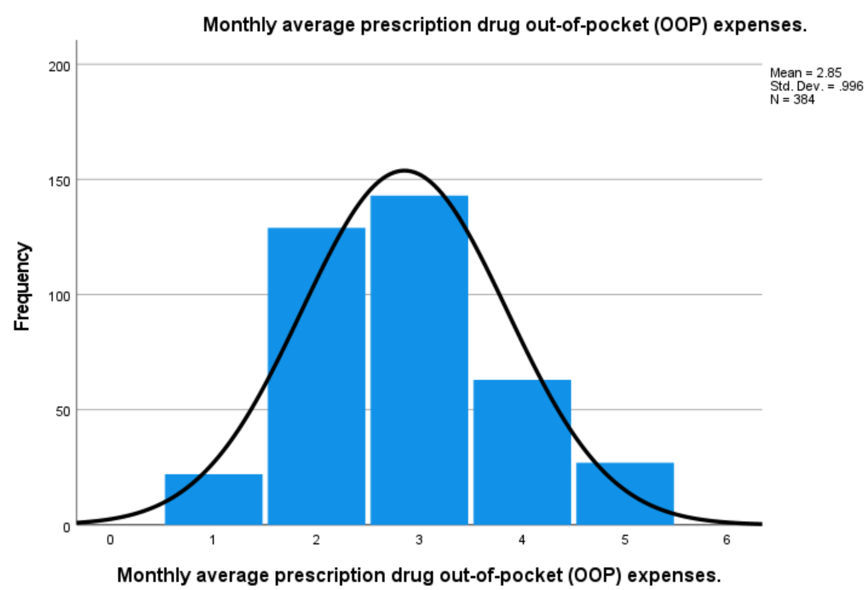


Figure 3

Histogram of the Participant's Self-Reported Monthly Average Prescription OOP Expenses Score



Research Questions Result: Statistical Analysis and Assumptions Testing

Research Question 1a - A binomial logistic regression statistics were performed to test the significance of the association between the monthly OOP expenses and odds of reporting medication purchases over the internet (survey question 12 checklist) in T2D adults controlling for demographics (Race, Age, Gender) and socioeconomic (Income, Education) variables. Linearity of the continuous variables to the dependent variable's logit was assessed via the Box-Tidwell (1962) procedure. A Bonferroni correction was applied using all 11 terms in the model, resulting in accepted statistical significance when $p < .00454$ (Tabachnick & Fidell, 2014). All continuous independent variables were linearly related to the dependent variable's logit based on this assessment. There was no standardized residual with a value of more than 2.5 standard deviations in the analysis. No significant outlier or leverage point was found. I determined that the assumptions were met. The logistic regression model was not statistically significant, $\chi2(4) = 21.368$, $p = .002$ instead of $p <.001$. However, I also checked the SPSS analysis of the model's adequacy to analyze how poor the model predicts the categorical outcomes using the Hosmer and Lemeshow goodness of fit test. The Hosmer and Lemeshow test is not statistically significant ($p = .821$), indicating that the model is not poorly fit (Laerd statistics, 2017). The model explained 7.5% (Nagelkerke R^2) of the variance in purchasing medication over the internet and correctly classified 58.8% of cases. The model participants' category prediction for sensitivity ("Used" category) was 46.3%, specificity ("Not Used" category) was 70.3%, positive predictive value (correctly predicted cases as "Used") was 59%, and negative predictive value (correctly predicted cases as "Not Used") was 58.7%. I also checked the model predicted probability, assessing the overall discrimination ability. The area under the ROC (Receiver Operation Characteristics) curve was .623, 95% CI [.566, .680], which is about an acceptable level of discrimination, according to Hosmer et al. (2013).

As shown in Table 9, the Wald test determined the statistical significance when all variables were included in the model. Only two were statistically significant of the six predictor variables: age and education. However, while controlling for demographic (age, race, gender) and socioeconomic (income, education) factors that could influence the result, the odds ratio for monthly OOP expenses was .86, 95% Cl [.69, 1.07], $p \geq .05$. Thus, when $p = .166$, increasing monthly OOP expenses are not significantly associated with a reduced likelihood of purchasing medication over the internet in the last 12 months, indicating that I could not reject the null hypothesis (H_o1a).

Table 9

Binomial Logistic Regression Predicting Likelihood of Purchasing Medication Over the Internet Cost-Savings Strategy Based on Monthly Average Prescription OOP Expenses

	B	SE.	Wald	df	Sig.	Odds ratio	95% CI for Odds ratio	
							Lower	Upper
Age	.27	.13	4.76	1	.029	1.31	1.03	1.68
Gender	-.10	.23	.19	1	.656	.90	.58	1.41
Education	.65	.20	10.61	1	.001	1.92	1.29	2.84
Race	-.10	.24	.17	1	.677	.90	.56	1.46
Income	-.07	.16	.19	1	.657	.93	.69	1.27
Monthly average OOP expenses	-.16	.11	1.92	1	.166	.86	.69	1.07
Constant	-3.34	1.25	7.17	1	.007	.04		

Note. Variable of interest is the Monthly average prescription drug OOP expenses. Age, Gender, Education, Race, and Income are covariable perceived to influence the outcome.

Research Question 1b - A binomial logistic regression statistics were performed to test the significance of the association between the monthly OOP expenses and odds of reporting Purchase of medication from other countries (survey question 12 checklist) in T2D adults controlling for demographics (Race, Age, Gender) and socioeconomic (Income, Education) variables. Linearity of the continuous variables to each dependent variable's logit was assessed via the Box-Tidwell (1962) procedure. A Bonferroni correction was applied using all 11 terms in the model, resulting in accepted statistical significance when $p < .00454$ (Tabachnick & Fidell, 2014). All continuous independent variables were linearly related to the dependent variable's logit based on this assessment. There was no standardized residual with a value of more than 2.5 standard deviations in the analysis. No significant outlier was found. Assumptions of outliers and significant leverage points were met. The logistic regression model was not statistically significant, $\chi2(4) = 15.191$, $p = .016$ instead of $p <.001$. However, SPSS also assesses the model's adequacy, analyzing how poor the model predicts the categorical outcomes using the Hosmer and Lemeshow goodness of fit test. The Hosmer and Lemeshow test is not statistically significant ($p = .326$), indicating that the model is not poorly fit. The model explained 5.4% (Nagelkerke R^2) of the variance in purchasing medication from other countries and correctly classified 57.6% of cases. Sensitivity was 56.7%, specificity was 58.5%, positive predictive value was 56.6%, and negative predictive value was 58.51%. The area under the ROC curve was .614, 95% CI [.571, .671], which is about an acceptable level of discrimination (model predicted probability), according to Hosmer et al. (2013). Only two of the six predictor variables were statistically significant: Race $p =$

.021 and monthly OOP expenses *p* =.005. As shown in Table 10 below, when all variables were included in the model, the odds ratio for monthly OOP expenses was .73, 95% Cl [.58, .91], *p* <.05. Thus, when *p* = .005, the monthly OOP expenses are significantly associated with the odds of purchasing medication from other countries among the participant's responses in the last 12 months while controlling for demographic (age, race, gender) and socioeconomic (income, education) factors, an indication that the null hypothesis would be rejected, and the alternative hypothesis accepted ($H_1$1b). However, the negative coefficient effect for increasing OOP expenses predicted a reduced likelihood of purchasing medication from other countries, contradicting the reasoned action approach model used to explain the study.

Table 10

Binomial Logistic Regression Predicting Likelihood of Purchasing Medication From Other Countries Cost-Savings Strategy Based on Monthly Average Prescription OOP Expenses

	B	SE.	Wald	df	Sig.	Odds ratio	95% CI for Odds ratio	
							Lower	Upper
Age	.04	.12	.11	1	.743	1.04	.82	1.32
Gender	.04	.23	.03	1	.858	1.04	.67	1.62
Education	-.06	.18	.10	1	.748	.94	.66	1.34
Race	-.56	.24	5.33	1	.021	.57	.36	.92
Income	-.03	.16	.031	1	.860	.97	.72	1.32
Monthly average OOP expenses	-.32	.11	7.72	1	.005	.73	.58	.91
Constant	1.47	1.16	1.59	1	.21	4.34		

Note. Variable of interest is the Monthly average prescription drug OOP expenses. Age, Gender, Education, Race, and Income are covariable perceived to influence the outcome.

Research Question 1c – A binomial logistic regression statistics were performed to test the significance of the association between the monthly OOP expenses and odds of reporting Obtaining free samples from doctors or patients assistance programs (survey question 12 checklist) in Type-2 Diabetes (T2D) adults while controlling for demographics (Race, Age, Gender) and socioeconomic (Income, Education) variables. Linearity of the continuous variables to each dependent variable's logit was assessed via the Box-Tidwell (1962) procedure. A Bonferroni correction was applied using all 11 terms in the model, resulting in accepted statistical significance when $p < .00454$ (Tabachnick & Fidell, 2014). All continuous independent variables were linearly related to the dependent variable's logit based on this assessment. There was no standardized residual with a value of more than 2.5 standard deviations in the analysis. No outlier was found. Assumption of significant outlier and leverage point was met. The logistic regression model was not statistically significant, $\chi2(4) = 5.178$, $p = .521$ ($p \leq .001$). However, SPSS also assesses the model's adequacy, analyzing how poor the model predicts the categorical outcomes using the Hosmer and Lemeshow goodness of fit test. The Hosmer and Lemeshow test is not statistically significant ($p = .760$), indicating that the model is not poorly fit. The model explained 2.0% (Nagelkerke R^2) of the variance in purchasing medication from other countries and correctly classified 73.4% of cases. The model participants' category prediction for sensitivity ("Used" category) was 0.0%, specificity ("Not Used" category) was 100%, positive predictive value (correctly predicted cases as "Used") was 0.0%, and negative predictive value (correctly predicted cases as "Not Used") was 73.4%. I also assessed the overall discrimination ability of the model. The area under the ROC curve was .571, 95% CI [.505, .638], which is poor discrimination (model predicted probability), according to Hosmer et al. (2013). None of the six predictor variables were statistically significant (as shown in Table 11), indicating that none of the independent variables contributed significantly to the variance explained in purchasing medication from other countries.

As shown in Table 11 below, when all variables were included in the model, the odds ratio for monthly OOP expenses was 1.07, 95% Cl [.84, 1.37], $p \geq .05$, indicating that increase in out of pocket could increase the odds of obtaining free samples from the Doctors or patient assistance program. Nevertheless, when $p = .587$, the monthly OOP expenses are not significantly associated with the odds of obtaining free samples from the Doctors or patient assistance program in the last 12 months while controlling for demographic (age, race, gender) and socioeconomic (income, education) factors. I determined that the null hypothesis would be accepted, and the alternative hypothesis rejected.

Table 11

Binomial Logistic Regression Predicting the Likelihood of Obtaining Free Samples From Doctors or Patients Assistance Programs Cost-Savings Strategy Based on Monthly Average Prescription OOP Expenses

	B	SE.	Wald	df	Sig.	Odds ratio	95% CI for Odds ratio	
							Lower	Upper
Age	-.15	.14	1.09	1	.296	.86	.66	1.14
Gender	.27	.26	1.09	1	.296	1.31	.79	2.17
Education	-.14	.19	.49	1	.483	.87	.60	1.28
Race	-.20	.26	.56	1	.455	.82	.49	1.38
Income	.17	.17	1.01	1	.314	1.19	.85	1.67
Monthly average OOP expenses	.07	.13	.30	1	.587	1.07	.84	1.37
Constant	-.59	1.26	.22	1	.638	.55		

Note. Variable of interest is the Monthly average prescription drug out-of-pocket (OOP) expenses. Age, Gender, Education, Race, and Income are covariable perceived to influence the outcome.

Research Question 1d - A binomial logistic regression statistics will be run to test the significance of the association between the monthly OOP expenses and odds of reporting split pills or changing the dosage frequency (survey question 12 checklist) in T2D adults controlling for demographics (Race, Age, Gender) and socioeconomic (Income, Education) variables. Linearity of the continuous variables to each dependent variable's logit was assessed via the Box-Tidwell (1962) procedure. A Bonferroni correction was applied using all 11 terms in the model, resulting in accepted statistical significance when $p < .00454$ (Tabachnick & Fidell, 2014). Based on this assessment, all continuous independent variables were linearly related to the dependent variable's logit. There was no standardized residual with a value of more than 2.5 standard deviations in the analysis. No significant outlier or leverage point was found. I considered the assumption met. The logistic regression model was not statistically significant, $\chi 2(4) = 9.356$, $p = .155$ ($p <.001$). However, SPSS also assesses the model's adequacy, analyzing how poor the model predicts the categorical outcomes using the Hosmer and Lemeshow goodness of fit test. The Hosmer and Lemeshow test is not statistically significant ($p = .524$), indicating that the model is not poorly fit. The model explained 5.4% (Nagelkerke R^2) of the variance in splitting pills or changing dosage frequency and correctly classified 90.5% of cases. The model participants' category prediction for sensitivity ("Used" category) was 0.0%, specificity ("Not Used" category) was 100%, positive predictive value (correctly predicted cases as "Used") was 0.0%, and negative predictive value (correctly predicted cases as "Not Used") was 73.4%. I also assessed the overall discrimination ability of the model. The area under the ROC curve was .641, 95% CI

[.539, .742], which is about an acceptable level of discrimination (model predicted probability), according to Hosmer et al. (2013). Of the six predictor variables, only monthly OOP expenses were statistically significant. As shown in Table 12, when all variables were included in the model, the odds ratio for monthly OOP expenses was 1.64, 95% Cl [1.15, 2.34], $p < .05$. Thus, when $p = .007$, an indication that increases in monthly OOP expenses are significantly associated with the increased likelihood of splitting pills or changing dosage frequency in the last 12 months while controlling for demographic (age, race, gender) and socioeconomic (income, education) factors. Based on these results, I determined that the null hypothesis would be rejected, and the alternative hypothesis accepted. Thus, higher OOP predicted an increase in the likelihood of splitting pills or changing dosage frequency.

Table 12

Binomial Logistic Regression Predicting Likelihood of Splitting Pills or Change Dosage Frequency Cost-Savings Strategy Based on Monthly Average Prescription OOP Expenses

	B	SE.	Wald	df	Sig.	Odds ratio	95% CI for Odds ratio	
							Lower	Upper
Age	.14	.20	.52	1	.473	1.15	.79	1.69
Gender	.12	.39	.10	1	.749	1.13	.53	2.43
Education	.27	.31	.77	1	.379	1.31	.72	2.39
Race	-.11	.40	.07	1	.787	.90	.41	1.97
Income	.04	.24	.02	1	.882	1.04	.64	1.67
Monthly average OOP expenses	.49	.18	7.35	1	.007	1.64	1.15	2.34
Constant	-5.58	2.02	7.60	1	.006	.004		

Note. Variable of interest is the Monthly average prescription drug out-of-pocket (OOP) expenses. Age, Gender, Education, Race, and Income are co-variables perceived to influence the outcome.

Research Question 2a – A binomial logistic regression statistics were performed to test the significance of the association between the monthly number of prescribed medications and odds of reporting purchase of medication over the internet (survey question 12 checklist) in T2D adults controlling for demographics (Race, Age, Gender) and socioeconomic (Income, Education) variables. Linearity of the continuous variables to each dependent variable's logit was assessed via the Box-Tidwell (1962) procedure. A Bonferroni correction was applied using all 11 terms in the model, resulting in accepted statistical significance when $p < .00454$ (Tabachnick & Fidell, 2014). Based on this assessment, all continuous independent variables were linearly related to the dependent variable's logit. There was no standardized residual with a value of more than 2.5 standard deviations in the analysis. No significant outlier and leverage point was found. The logistic regression model was not statistically significant, $\chi 2(4) = 21.427$, when $p = .002$ ($p < .001$). However, determine the overall statistical significance of the binomial logistic regression model on how well the model does not fit using the Hosmer and Lemeshow goodness of fit test ($p = .670$), which indicated that the model is significantly fit to predict categorical outcomes (Laerd Statistics, 2017). The model explained 7.5% (Nagelkerke R^2) of the variance in purchasing medication over the internet and correctly classified 59.6% of cases. Sensitivity was 50.3%, specificity was 68.2%, positive predictive value was 59.3%, and negative predictive value was 59.8%. The area under the ROC curve was .617, 95% CI [.560, .674], which is about an acceptable level of discrimination (model predicted probability), according to Hosmer et al. (2013). Only two were statistically significant of the six predictor variables: age and education (Table

13), indicating that the addition of these two covariables contributed significantly to the variation explained in the odds of purchasing medication over the internet.

Nevertheless, while controlling for demographic (age, race, gender) and socioeconomic (income, education) factors, as shown in Table 13 below, when all variables were included in the model, the odds ratio for monthly numbers of prescribed medication was .86, 95% Cl [.70, 1.05]. Thus, when *p* = .137, increasing monthly numbers of prescribed medication are not statistically significantly associated with a reduced likelihood of purchasing medication over the internet in the last 12 months, indicating that the null hypothesis would be accepted, and the alternative hypothesis rejected.

Table 13

Binomial Logistic Regression Predicting the Likelihood of Purchase Medication Over the Internet Cost-Savings Strategy Based on the Average Monthly Number of Prescribed Medication

	B	SE.	Wald	df	Sig.	Odds ratio	95% CI for Odds ratio	
							Lower	Upper
Age	.26	.13	4.40	1	.036	1.30	1.02	1.66
Gender	-.12	.23	.27	1	.607	.89	.57	1.39
Education	.64	.20	10.24	1	.001	1.90	1.28	2.81
Race	-.15	.24	.39	1	.530	.86	.53	1.38
Income	-.12	.15	.60	1	.439	.89	.66	1.20
Monthly number of prescribed medication	-.16	.11	2.21	1	.137	.86	.70	1.05
Constant	-3.01	1.27	5.61	1	.018	.05		

Note. The variable of interest is the Monthly number of prescribed medications. Age, Gender, Education, Race, and Income are co-variables perceived to influence the outcome.

Research Question 2b - A binomial logistic regression statistics were performed to test the significance of the association between the monthly number of prescribed medications and odds of reporting Purchase of medication from other countries (survey question 12 checklist) in T2D adults controlling for demographics (Race, Age, Gender) and socioeconomic (Income, Education) variables. The logistic regression model was not statistically significant, $\chi 2(4) = 16.628$, when $p = .011$ ($p < .001$). However, I determine the overall statistical significance of the binomial logistic regression model on how well the model does not fit using the Hosmer and Lemeshow goodness of fit test ($p = .015$), which indicated that the model is significantly fit to predict categorical outcomes (Laerd Statistics, 2017). The model explained 5.9% (Nagelkerke R^2) of the variance in purchasing medication from other countries and correctly classified 58.4% of cases. Sensitivity was 49.7%, specificity was 66.8%, positive predictive value was 59.2%, and negative predictive value was 57.87%. The area under the ROC curve was .627, 95% CI [.570, .685], which is about an acceptable level of discrimination (model predicted probability), according to Hosmer et al. (2013). Only two were statistically significant of the six predictor variables: race (p =.013) and a monthly number of prescribed medication ($p = .003$) (Table 14).

As shown in Table 14 below, when all variables were included in the model, the odds ratio for monthly numbers of prescribed medication was .73, 95% Cl [.59, .90], $p < .05$. Thus, when $p = .003$, an increased monthly numbers of prescribed medication are statistically significantly associated with a reduced likelihood of purchasing medication from other countries in the last 12 months while controlling for demographic (age, race, gender) and socioeconomic (income, education) factors. I determined that the null hypothesis would be rejected based on these results. However, the negative coefficient effect of an increased number of prescribed medications predicts a lower odds of purchasing medication from other countries, which contradicts the reasoned action theory.

Table 14

Binomial Logistic Regression Predicting the Likelihood of Purchase Medication From Other Countries Cost-Savings Strategy Based on the Average Monthly Number of Prescribed Medication

	B	SE.	Wald	df	Sig.	Odds ratio	95% CI for Odds ratio	
							Lower	Upper
Age	.06	.12	.22	1	.640	1.06	.83	1.34
Gender	.05	.23	.04	1	.837	1.05	.67	1.63
Education	-.07	.18	.16	1	.692	.93	.65	1.33
Race	-.60	.24	6.17	1	.013	.55	.34	.88
Income	-.10	.15	.44	1	.505	.90	.67	1.22
Monthly number of prescribed medication	-.32	.11	8.88	1	.003	.73	.59	.90
Constant	1.88	1.20	2.44	1	.118	6.52		

Note. The variable of interest is the Monthly number of prescribed medications. Age, Gender, Education, Race, and Income are co-variables perceived to influence the outcome.

Research Question 2c - A binomial logistic regression statistics were performed to test the significance of the association between the monthly number of prescribed medications and odds of reporting obtaining free samples from doctors or patients assistance programs (survey question 12 checklist) in T2D adults controlling for demographics (Race, Age, Gender) and socioeconomic (Income, Education) variables. Linearity of the continuous variables to each dependent variable's logit was assessed via the Box-Tidwell (1962) procedure. A Bonferroni correction was applied using all 11 terms in the model, resulting in accepted statistical significance when $p < .00454$ (Tabachnick & Fidell, 2014). Based on this assessment, all continuous independent variables were linearly related to the dependent variable's logit. There was no standardized residual with a value of more than 2.5 standard deviations in the analysis. No significant outliers and leverage point was found. The logistic regression model was not statistically significant, $\chi2(4) = 6.502$, p = .464 ($p < .001$). However, assess the model's adequacy, analyzing how poor the model predicts the categorical outcomes using the Hosmer and Lemeshow goodness of fit test. The Hosmer and Lemeshow test is not statistically significant ($p = .760$), indicating that the model is not poorly fit. The model explained 2.6% (Nagelkerke R^2) of the variance in purchasing medication from other countries and correctly classified 73.4% of cases. Sensitivity was 0.0%, specificity was 100%, positive predictive value was 0.0%, and negative predictive value was 73.4%. The area under the ROC curve (Figure 42) was .572, 95% CI [.505, .638], which is considered poor discrimination (model predicted probability), according to Hosmer et al. (2013). None of the six predictor variables were statistically significant (Table 15), indicating that none of the variables changed the variance of obtaining free samples from a doctor or patient assistance program.

However, as shown in Table 15 below, when all variables were included in the model, the odds ratio for monthly numbers of prescribed medication was 1.17, 95% Cl [.94, 1.47], an indication that an increase in monthly numbers of prescribed medication increases the odds of obtaining free samples from a doctor or patient assistance program. Nevertheless, when $p = .167$, monthly numbers of prescribed medication are not statistically significantly associated with the odds of obtaining free samples from a doctor or patient assistance program in the last 12 months while controlling for demographic (age, race, gender) and socioeconomic (income, education) factors. Based on these results, I accepted the null and rejected alternative hypotheses.

Table 15

Binomial Logistic Regression Predicting the Likelihood of Obtaining Free Samples From Doctors or Patients Assistance Programs Cost-Savings Strategy Based on the Average Monthly Number of Prescribed Medications

	B	SE.	Wald	df	Sig.	Odds ratio	95% CI for Odds ratio	
							Lower	Upper
Age	-.13	.14	.85	1	.356	.88	.67	1.16
Gender	.28	.26	1.15	1	.283	1.32	.80	2.19
Education	-.11	.19	.34	1	.558	.89	.61	1.31
Race	-.14	.27	.28	1	.595	.87	.52	1.46
Income	.20	.17	1.44	1	.230	1.22	.88	1.70
Monthly number of prescribed medication	.16	.16	1.91	1	.167	1.17	.94	1.47
Constant	-1.20	1.30	.86	1	.355	.30		

Note. The variable of interest is the Monthly number of prescribed medications. Age, Gender, Education, Race, and Income are co-variables perceived to influence the outcome.

Research Question 2d - A binomial logistic regression statistics will be run to test the significance of the association between the monthly number of prescribed medications and odds of reporting split pills or changing the dosage frequency (survey question 12 checklist) in T2D adults controlling for demographics (Race, Age, Gender) and socioeconomic (Income, Education) variables. Linearity of the continuous variables to each dependent variable's logit was assessed via the Box-Tidwell (1962) procedure. A Bonferroni correction was applied using all 11 terms in the model, resulting in accepted statistical significance when $p < .00454$ (Tabachnick & Fidell, 2014). Based on this assessment, all continuous independent variables were linearly related to the dependent variable's logit. There were 28 Cases with studentized residuals greater than 2.0

identified as a potential outlier which was kept in the analysis after log transformation was performed to correct the outliers, but there was no change in results. There was no standardized residual with a value of more than 2.5 standard deviations in the analysis. The assumptions were met. The logistic regression model was not statistically significant, $\chi 2(4) = 5.995$, p = .424 (*p* <.001). However, SPSS also assesses the model's adequacy, analyzing how poor the model predicts the categorical outcomes using the Hosmer and Lemeshow goodness of fit test. The Hosmer and Lemeshow test is not statistically significant (*p* = .524), indicating that the model is not poorly fit. The model explained 3.5% (Nagelkerke R^2) of the variance in splitting pills or changing dosage frequency and correctly classified 90.5% of cases. Sensitivity was 0.0%, specificity was 100%, positive predictive value was 0.0%, and negative predictive value was 90.5%. The area under the ROC curve was .620, 95% CI [.527, .714], which is about an acceptable level of discrimination (model predicted probability), according to Hosmer et al. (2013). Of the six predictor variables, only the monthly number of prescribed medications was statistically significant (Table 16).

As shown in Table 16 below, when all variables were included in the model, the odds ratio for monthly numbers of prescribed medication was 1.41, 95% Cl [1.01, 1.98], *p* <.05, indicating that increases in monthly numbers of prescribed medication increase the odds of splitting pills or changing dosage frequency. Thus, when *p* = .044, monthly numbers of prescribed medication are statistically significantly associated with the odds of splitting pills or changing dosage frequency in the last 12 months while controlling for demographic (age, race, gender) and socioeconomic (income, education) factors among adults with T2D. Based on these results, I determined that the null hypothesis would be rejected, and the alternative hypothesis accepted.

Table 16

Binomial Logistic Regression Predicting Likelihood of Splitting Pills or Change Dosage Frequency Cost-Savings Strategy Based on the Average Monthly Number of Prescribed Medications

	B	SE.	Wald	df	Sig.	Odds ratio	95% CI for Odds ratio	
							Lower	Upper
Age	.14	.20	.49	1	.486	1.18	.78	1.69
Gender	.16	.39	.18	1	.672	1.18	.55	2.51
Education	.29	.31	.87	1	.350	1.34	.73	2.45
Race	-.05	.40	.02	1	.899	.95	.44	2.07
Income	.16	.25	.42	1	.517	1.17	.72	1.91
Monthly number of prescribed medication	.35	.17	4.05	1	.044	1.41	1.01	1.98
Constant	-5.76	2.11	7.43	1	.006	.003		

Note. The variable of interest is the Monthly number of prescribed medications. Age, Gender, Education, Race, and Income are co-variables perceived to influence the outcome.

Research Question 3a - A binomial logistic regression statistics were performed to test the significance of the association between the participant's health insurance status and odds of reporting purchase of medication over the internet (survey question 12 checklist) in T2D adults controlling for demographics (Race, Age, Gender) and socioeconomic (Income, Education) variables. Linearity of the continuous variables to each dependent variable's logit was assessed via the Box-Tidwell (1962) procedure. A Bonferroni correction was applied using all 10 terms in the model, resulting in accepted statistical significance when $p < .005$ (Tabachnick & Fidell, 2014). Based on this assessment, all continuous independent variables were linearly related to the dependent variable's logit. There was no standardized residual with a value of more than 2.5

standard deviations in the analysis. No significant outlier or leverage point was found. I determined that the assumptions were met. The logistic regression model was statistically significant, $\chi2(4) = 27.717$, $p < .001$, the Hosmer and Lemeshow test was not statistically significant (p = .112), indicating that the model is not a poor fit. The model explained 9.8% (Nagelkerke R^2) of the variance in purchasing medication over the internet and correctly classified 52.2% of cases. Sensitivity was 42.5%, specificity was 67.9%, positive predictive value was 54.8%, and negative predictive value was 39.2%. The area under the ROC curve was .631, 95% CI [.574, .687], which is about an acceptable level of discrimination (model predicted probability), according to Hosmer et al. (2013). Of the six predictor variables, only two were statistically significant: education (p =.001) and health Insurance status (p = .021) (Table 17), indicating that these two variables contributed significantly to the variance of purchasing medication over the internet.

As shown in Table 17 below, when all variables were included in the model, the odds ratio for participants' health insurance status was 12.06, 95% Cl [1.45, 100.48], p <.05. Thus, when p = .021, having health insurance is statistically significantly associated with an increased likelihood of purchasing medication over the internet in the last 12 months than not having among self-reported adults diagnosed with T2D while controlling for demographic (age, race, gender) and socioeconomic (income, education) factors. I determined that the null hypothesis would be rejected, and the alternative hypothesis accepted.

Table 17

Binomial Logistic Regression Predicting Likelihood of Purchasing Medication Over the Internet Strategy Based on Health Insurance Status

	B	SE.	Wald	df	Sig.	Odds ratio	95% CI for Odds ratio	
							Lower	Upper
Age	.24	.13	3.48	1	.062	1.27	.99	1.62
Gender	-.09	.23	.14	1	.710	.92	.59	1.44
Education	.71	.21	11.13	1	.001	2.04	1.34	3.10
Race	-.12	.25	.22	1	.637	.89	.55	1.44
Income	-.14	.16	.81	1	.369	.87	.64	1.18
Health insurance Status	2.49	1.08	5.30	1	.021	12.06	1.45	100.48
Constant	-6.28	1.75	12.82	1	.000	.002		

Note. The variable Health Insurance Status is categorical "Yes" compared to "No." Age, Gender, Education, Race, and Income are co-variables perceived to influence the outcome.

Research Question 3b - A binomial logistic regression statistics were performed to test the significance of the association between the health insurance status and odds of reporting Purchase of medication from other countries (survey question 12 checklist) in T2D adults controlling for demographics (Race, Age, Gender) and socioeconomic (Income, Education) variables. Linearity of the continuous variables to each dependent variable's logit was assessed via the Box-Tidwell (1962) procedure. Linearity of the continuous variables to each dependent variable's logit was assessed via the Box-Tidwell (1962) procedure. A Bonferroni correction was applied using all 10 terms in the model, resulting in accepted statistical significance when $p < .005$ (Tabachnick & Fidell, 2014). Based on this assessment, all continuous independent variables were linearly related to the dependent variable's logit. There was no standardized residual with a value of more than 2.5 standard deviations in the analysis. No significant outlier or leverage point was found. I determined that the assumptions were met. The logistic regression model was not statistically significant, $\chi2(4) = 8.745$, p =.188 ($p < .001$). However, the Hosmer and Lemeshow tests are not statistically significant ($p = .629$), indicating that the model is not poorly fit. The model explained 3.2% (Nagelkerke R^2) of the variance in purchasing medication from other countries and correctly classified 57.3% of cases. Sensitivity was 38.5%, specificity was 75.5%, positive predictive value was 60.5%, and negative predictive value was 55.8%. The area under the ROC curve was .585, 95% CI [.527, .644], which is about an acceptable level of discrimination (model predicted probability), according to Hosmer et al. (2013). Only race (p =.010) was statistically significant (Table 18), indicating that the covariable contributed to the variance in the model.

As shown in Table 18 below, when all variables were included in the model, the odds ratio for participants' health insurance status was .51, 95% Cl [.14, 1.78]. Thus, when $p = .289$, having health insurance is not statistically significantly associated with the odds of reporting purchasing medication from other countries than not having health insurance at all in the last 12 months among self-reported adults diagnosed with T2D while controlling for demographic (age, race, gender) and socioeconomic (income, education) factors. Based on these results, I determined that the null hypothesis would be accepted, and the alternative hypothesis rejected.

Table 18

Binomial Logistic Regression Predicting the Likelihood of Purchasing Medication From Other Countries Cost-Savings Strategy Based on Health Insurance Status

	B	SE.	Wald	df	Sig.	Odds ratio	95% CI for Odds ratio	
							Lower	Upper
Age	.02	.12	.03	1	.858	1.02	.81	1.29
Gender	.02	.23	.01	1	.938	1.02	.66	1.58

Education	-.04	.18	.06	1	.811	.96	.67	1.37
Race	-.62	.24	6.67	1	.010	.54	.33	.86
Income	-.13	.15	.76	1	.383	.88	.65	1.18
Health insurance Status	-.68	.64	1.12	1	.289	.51	.14	1.78
Constant	1.53	1.34	1.31	1	.253	4.61		

Note. The variable Health Insurance Status is categorical "Yes" compared to "No." Age, Gender, Education, Race, and Income are co-variables perceived to influence the outcome.

Research Question 3c - A binomial logistic regression statistics were performed to test the significance of the association between the health insurance status and odds of reporting obtaining free samples from doctors or patients assistance programs (survey question 12 checklist) in T2D adults while controlling for demographics (Race, Age, Gender) and socioeconomic (Income, Education) variables. Linearity of the continuous variables to each dependent variable's logit was assessed via the Box-Tidwell (1962) procedure. A Bonferroni correction was applied using all 10 terms in the model, resulting in accepted statistical significance when $p < .005$ (Tabachnick & Fidell, 2014). Based on this assessment, all continuous independent variables were linearly related to the dependent variable's logit. There was no standardized residual with a value of more than 2.5 standard deviations in the analysis. No significant outlier or leverage point was found. I determined that the assumptions were met. The logistic regression model was not statistically significant, $\chi2(4) = 5.189$, p =.520 ($p < .001$). However, the Hosmer and Lemeshow tests are not statistically significant ($p = .488$), indicating that the model is not poorly fit. The model explained 2.1% (Nagelkerke R^2) of the variance in obtaining free medication from the Doctors or patients assistance program and correctly classified 73.3% of cases. Sensitivity was 0.0%, specificity was 100%, positive predictive value was 0.0%, and negative predictive value was 73.2%. The area under the ROC curve was .560, 95% CI [.492, .629], which is considered poor discrimination (model predicted probability), according to Hosmer et al. (2013). None of the six predictor variables were statistically significant (Table 19). As shown in Table 19 below, when all variables were included in the model, the odds ratio for participants' health insurance status was .98, 95% Cl [.25, 3.82]. Thus, when $p = .978$, having health insurance is not statistically significantly associated with the likelihood of obtaining a free sample from Doctors or patient assistance programs than not having health insurance in the last 12 months among self-reported adults diagnosed with T2D while controlling for demographic (age, race, gender) and socioeconomic (income, education) factors. I determined that the null hypothesis would be accepted and the alternative hypothesis rejected.

Table 19

Binomial Logistic Regression Predicting the Likelihood of Obtaining Free Samples From Doctors or Patients Assistance Program Cost-Savings Strategy Based on Health Insurance Status

	B	SE.	Wald	df	Sig.	Odds ratio	95% CI for Odds ratio	
							Lower	Upper
Age	-.09	.14	.45	1	.501	.91	.70	1.19
Gender	.29	.26	1.29	1	.257	1.34	.81	2.22
Education	-.17	.20	.71	1	.398	.85	.58	1.25
Race	-.16	.27	.35	1	.555	.85	.51	1.44
Income	.22	.17	1.75	1	.186	1.25	.90	1.74
Health insurance Status	-.02	.69	.001	1	.978	.98	.25	3.82
Constant	-.51	1.44	.13	1	.721	.60		

Note. The variable Health Insurance Status is Categorical "Yes" compared to "No." Age, Gender, Education, Race, and Income are co-variables perceived to influence the outcome.

Research Question 3d- A binomial logistic regression statistics were performed to test the significance of the association between the health insurance status and odds of reporting split pills or changing the dosage frequency (survey question 12 checklist) in T2D adults controlling for demographics (Race, Age, Gender) and socioeconomic (Income, Education) variables. Linearity of the continuous variables to each dependent variable's logit was assessed via the Box-Tidwell (1962) procedure. A Bonferroni correction was applied using all 10 terms in the model, resulting in accepted statistical significance when $p < .005$ (Tabachnick & Fidell, 2014). Based on this assessment, all continuous independent variables were linearly related to the dependent variable's logit. There was no standardized residual with a value of more than 2.5 standard deviations in the analysis. No significant outlier or leverage point was found. I determined that the assumptions were met. The logistic regression model was not statistically significant, $\chi2(4) = 5.102$, $p = .531$ ($p < .001$). However, the Hosmer and Lemeshow tests are not statistically significant ($p = .833$), indicating that the model is not poorly fit. The model explained 3.0% (Nagelkerke R^2) of the variance in splits pills or change dosage frequency and correctly classified 90.7% of cases. Sensitivity was 0.0%, specificity was 100%, positive predictive value was 0.0%, and negative predictive value was 90.6%. The area under the ROC curve was .583, 95% CI [.479, .688], which is considered poor discrimination (model predicted probability), according to Hosmer et al. (2013). None of the six predictor variables were statistically significant (Table 20).

As shown in Table 20 below, when all variables were included in the model, the odds ratio for participants' health insurance status was .27, 95% Cl [.07, 1.08]. Thus, when $p = .063$, having health insurance is not statistically significantly associated with the odds of reporting splitting pills or changing dosage frequency than having no health insurance at all in the last 12 months among self-reported adults diagnosed with T2D while controlling for demographic (age, race, gender) and socioeconomic (income, education) factors. Based on these results, I determined that the null hypothesis would be accepted, and the alternative hypothesis rejected.

Table 20

Binomial Logistic Regression Predicting Likelihood of Splitting Pills or Change Dosage Frequencies Cost-Savings Strategy Based on Health Insurance Status

	B	SE.	Wald	df	Sig.	Odds ratio	95% CI for Odds ratio	
							Lower	Upper
Age	.17	.19	.77	1	.381	1.18	.81	1.73
Gender	.097	.39	.06	1	.803	1.10	.51	2.37
Education	.22	.30	.51	1	.475	1.24	.69	2.23
Race	-.11	.40	.08	1	.777	.89	.41	1.96
Income	.19	.25	.58	1	.448	1.21	.74	1.99
Health insurance Status	-1.33	.76	3.45	1	.063	.27	.07	1.08
Constant	-2.98	2.08	2.05	1	.153	.05		

Note. The variable Health Insurance Status is categorical "Yes" compared to "No." Age, Gender, Education, Race, and Income are co-variables perceived to influence the outcome.

Research Question 4a – A Multiple regression statistics were run to predict the dependent variable (odds of Purchasing medication over the internet, question 13 (1) composite score) from the independent variables (insurance status, monthly OOP expenses, the monthly number of prescribed medication) among T2D adults controlling for demographics (Race, Age, Gender) and socioeconomic (Income, Education) variables. The assumption of linearity was assessed through visual inspection of the partial regression plots and a plot of studentized residuals against the predicted values. I also assessed the independence of residual assumption by checking the Durbin-Watson statistic value of the analysis, 1.854. While a value of approximately 2 indicates no correlation between residuals (Laerd Statistics, 2015), I accepted residuals were independent. The assumption of homoscedasticity of residuals was confirmed by visual inspection of a plot of studentized residuals versus unstandardized predicted values. Assessing the assumptions for multicollinearity of data and significant outliers, high leverage points, or highly influential points, I confirmed no tolerance values greater than 0.1. and studentized deleted residuals greater than ±3 standard deviations. I also confirmed that no leverage values were greater than 0.2 and Cook's distance value above 1. Also confirmed the assumption of normality by visual inspection of a Q-Q Plot. I determined that all the assumptions were met. Detailed analysis is provided in the exhibits (Appendix C).

As shown in Table 21 below, the *p*-value = .343 for the dependent variable (purchase medication over the internet) means $p > .05$. The multiple regression model did not statistically significantly predict the likelihood of purchasing medication over the Internet. It can also be deduced that not all the independent variables in the model (health insurance status, income, gender, monthly number of prescribed medications, race, age, education, monthly average prescription drug OOP expenses) did statistically significantly predict participants' likelihood to purchase medication over the internet if all medication costs cannot be met, $F(8, 355) = 1.128$, $p > .05$.

Table 21

Multiple Linear Regression Results: Model fit Anova[a] for Dependent Variable – Purchase Medication Over the Internet

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	8.684	8	1.086	1.128	.343[b]
	Residual	341.522	355	.962		
	Total	350.206	363			

a. Dependent Variable: Likelihood of Purchasing medication over the internet if all medication costs cannot be met
b. Predictors: (Constant), Independent variables: Health insurance status, Monthly number of prescribed medications, Monthly average OOP expenses, Co-variables: Income, Education, Race, Gender, Age.

The multiple regression results, as shown in Table 21b below, indicated that the intercept is statistically significant at .000 (i.e., $p < .0005$), meaning that it is different from 0 (zero) (Laerd Statistics, 2015). However, the slope coefficients "B" column of Table (21b) shows that the monthly number of prescribed medication = 0.025 and monthly OOP expenses = 0.026. The slope coefficient had been positive; an increase in the monthly number of prescribed medications (measured in numbers of prescribed medication) and an increase in monthly OOP expenses (measured in U.S.$) would have been associated with an increase in the likelihood of purchasing medication from internet. However, with $p = .646$, 95% CI [-0.083, 0.134] for the monthly number of prescribed medication variable and $p = .663$, 95% CI [-0.09, 0.14], for the monthly OOP expenses variable, indicating that the slope coefficient is not statistically significant (i.e., there is no linear relationship).

However, health insurance status is a categorical variable. According to Laerd Statistics (2015), the slope coefficient's value represents the dependent variable between the two categories of the variable. The two categories of the insurance status variable are coded as “1” = “Yes” having health insurance and “2” = “No” having no health insurance. The comparison between the two categories is to the category with a value of “2”. So, in this case, comparing having no health insurance “2” to having health insurance “1”.The value of slope coefficient is negative, -0.521, which means that predicted likelihood for having health insurance is far greater than that of having no health insurance to purchase medication over the internet. Also, the *p*-value is .021 (i.e., $p < .05$, *p* is less than .05), 95% CI [-0.242, -0.102]. I accepted that the slope coefficient is statistically significant for health insurance status; that is, the slope coefficient is different from 0 (zero) in the population (i.e., there is a linear relationship) (Laerd Statistics, 2015).

Overall, The multiple regression model did not statistically significantly predict the likelihood of purchasing medication over the Internet, F(3, 355) = 1.128, $p > .05$. The regression coefficients and standard errors, Table (22 below) adj. $R^2 = .003$, $R^2 =.025$, i.e., the overall model was 2.5% with an adjusted R^2 of 0.3%, a low size effect according to Cohen (1988). However, not all variables added statistically significantly to the prediction, $p < .05$. But health insurance status is associated at a statistically significant level with the prediction of purchasing medication over the internet (B = -67, *p* = < .05, 95% CI [-0.242, -0.102]) in T2D adults controlling for demographics (Race, Age, Gender) and socioeconomic (Income, Education) variables. Based on this result, I rejected the null hypothesis because one of the independent variables of interest (health insurance status) contributed statistically when all variables were included in the model. However, the strength of the variation in the proportion of the dependent variable (Likely to purchase medication over the internet) explained (0.3%) by all the independent variables is weak as measured by adjusted R-squared (.003).

Table 22

Multiple Regression Results for the Likelihood to Purchase Medication Over the Internet if all Medication Costs Cannot Be Met

Purchasing medication over the internet	B	95% CI for B		SE B	β	Adjusted R-squared	R-squared
		LL	UL				
Model						0.003	.025
Constant	4.81***	3.56	6.06	.64			
Monthly number of prescribed medications	.03	-.08	.13	.06	.03		
Monthly average prescription drug out-of-pocket (OOP) expenses	.03	-.09	.14	.06	.03		
Health insurance status	-.67*	-.24	-.10	.29	-.12*		
Gender	-.17	-.38	.05	.11	-.08		
Race	-.09	-.32	.14	.18	-.04		
Education	-.03	-.20	.14	.09	-.02		
Income	-.05	-.20	.10	.08	-.04		
Age	.02	-.10	.13	.06	.02		

Note. Model = “Enter” method in SPSS statistics; B = Unstandardized regression coefficients; CI = confidence interval; LL = lower limit; UL = upper limit; SE B = standard error of coefficients; β = standardized coefficient.

* $p < .05$, ** $p < .01$, *** $p < .001$

Research Question 4b - A Multiple regression statistics were run to predict the dependent variable (odds of Purchasing medication from other countries, question 13 (1) composite score) from the independent variables (insurance status, monthly OOP expenses, the monthly number of prescribed medication) among T2D adults controlling for demographics (Race, Age, Gender) and socioeconomic (Income, Education) variables. The assumption of linearity was assessed through visual inspection of the partial regression plots and a plot of studentized residuals against the predicted values. I also assessed the independence of residual assumption by checking the Durbin-Watson statistic value of the analysis, 1.773. While a value of approximately 2 indicates no correlation between residuals (Laerd Statistics, 2015), I accepted that the assumption is met. The assumption of homoscedasticity of residuals was confirmed by visual inspection of a plot of studentized residuals versus unstandardized predicted values. Assessing the assumptions for multicollinearity of data and significant outliers, high leverage points, or highly influential points, I confirmed no tolerance values greater than 0.1. and studentized deleted residuals greater than ±3 standard deviations. I also confirmed that no leverage values were greater than 0.2 and Cook's distance value above 1. Also confirmed the assumption of normality by visual inspection of a Q-Q Plot (Laerd Statistics, 2015). I determined that all assumptions were met. Detailed analysis is provided in the exhibits (Appendix C).

As shown in Table 23 below, the *p*-value = .014 for the dependent variable (likely to purchase medication from other countries) means $p < .05$. An indication that the multiple regression model did statistically significantly fit to predict the likelihood of purchasing medication from other countries. It can also be deduced that all the independent variables in the model (Health insurance status, Income, Gender, Monthly number of prescribed medications, Race, Age, Education, Monthly average prescription drug OOP expenses) did statistically significantly contribute to the model prediction of likelihood to purchase medication from other countries, $F(8, 355) = 2.430$, $p < .05$.

Though an adjusted R^2 of 3%, a low size effect, according to Cohen (1988), is still significant and indicates the coefficient's effect magnitude.

Table 23

Multiple linear regression results: Model fit Anova[a] for dependent variable – purchase medication from other countries

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	21.450	8	2.681	2.430	0.14[b]
	Residual	391.701	355	1.103		
	Total	413.151	363			

a. Dependent Variable: Likelihood of Purchasing medication from other countries if all medication costs cannot be met
b. Predictors: (Constant), Independent Variables: Health insurance status, Monthly number of prescribed medications, Monthly average OOP expenses, Co-variables: Income, Education, Race, Gender, Age.

The multiple regression results, as shown in Table 24 below, indicated that the intercept is statistically significant at .000 (i.e., $p < .0005$), meaning that it is different from 0 (zero) (Laerd Statistics, 2017). However, the slope coefficients "B" column of Table (21b) shows that the monthly number of prescribed medication = -.097 and monthly OOP expenses = -.089. As such, the slope coefficient had been negative; an increase in the monthly number of prescribed medications (measured in numbers of prescribed medications) and an increase in monthly OOP expenses (measured in U.S.$) would have been associated with a decrease in the likelihood of purchasing medication from other countries. However, with $p = .100$, 95% CI [-0.21, 0.02] for the monthly number of prescribed medication variable and $p = .162$, 95% CI [-0.21, 0.04], for monthly OOP expenses variable. I determine that the slope coefficient is not statistically significant, thus no linear relationship (Laerd Statistics, 2015).

However, health insurance status is a categorical variable. The slope coefficient's value represents the dependent variable between the two categories of the variable (Laerd Statistics, 2015). The two categories of the Insurance status variable are coded as "1" = "Yes" having health insurance and "2" = "No" having no health insurance. The comparison between the two categories is to the category with a value of "2". So, in this case, comparing having no health insurance "2" to having health insurance "1".The value of slope coefficient is negative, -0.08, which means that predicted likelihood for having no health insurance is far greater than that of having health insurance to purchase medication from other countries. Also, the *p*-value is.806 (i.e., $p < .05$, p is greater than .05), 95% CI [-0.69, -0.534]. I accepted that the slope coefficient is not statistically significant; that is, the slope coefficient is not different from 0 (zero) in the population (i.e., there is no linear relationship) (Laerd Statistics, 2015).

Overall, the multiple regression model statistically significantly predicts the likelihood of purchasing medication from other countries, $F(8, 355) = 2.430$, $p < .05$. The regression coefficients and standard errors, Table (24 below) adj. $R^2 = .03$, $R^2 =.05$, i.e., the R^2 for the overall model was 5% with an adjusted R^2 of 3%, a low size effect according to Cohen (1988). However, none of the variables added statistically significantly to the prediction, $p < .05$ with the prediction of purchasing medication from other countries model in T2D adults controlling for demographics (Race, Age, Gender) and socioeconomic (Income, Education) variables. This evidence suggests that other factors need to be considered. Based on this result, I accepted the null hypothesis because none of the independent variables of interest contributed at a statistically significant level when all variables were included in the model.

Table 24

Multiple Regression Results for the Likelihood to Purchase Medication From Other Countries if all Medication Costs Cannot Be Met

Purchasing medication from other countries	B	95% CI for B		SE B	β	Adjusted R-squared	R-squared
		LL	UL				
Model						0.03*	.05
Constant	5.10***	3.76	6.45	.68			
Age	.04	-.09	.16	.06	.03		
Gender	-.12	-.35	.11	.12	-.05		
Education	-.11	-.29	.07	.09	-.06		
Race	.23	-.02	.47	.13	.10		
Income	-.16	-.32	.001	.08	-.11		
Monthly number of prescribed medications	-.10	-.21	.02	.06	-.10		
Monthly average prescription drug out-of-pocket (OOP) expenses	-.10	-.21	.04	.06	-.08		
Health insurance status	-.08	-.69	.53	.31	-.01		

Note. Model = "Enter" method in SPSS statistics = unstandardized regression coefficients; CI = confidence interval; LL = lower limit; UL = upper limit; SE B = standard error of coefficients; β = standardized coefficient.

* $p < .05$, ** $p < .01$, *** $p < .001$

Research Question 4c- A Multiple regression statistics were run to predict the dependent variable (odds of obtaining medication from Doctors or patients assistance programs, question 13 (3) composite score) from the independent variables (insurance status, monthly OOP expenses, the monthly number of prescribed medication) among T2D adults controlling for demographics (Race, Age, Gender) and socioeconomic (Income, Education) variables. The assumption of linearity was assessed through visual inspection of the partial regression plots and a plot of studentized residuals against the predicted values. I also assessed the independence of residual assumption by checking the Durbin-Watson statistic value of the analysis, 1.854. While a value of approximately 2 indicates no correlation between residuals (Laerd Statistics, 2015), I accepted that the assumption is met. The assumption of homoscedasticity of residuals was confirmed by visual inspection of a plot of studentized residuals versus unstandardized predicted values. Assessing the assumptions for multicollinearity of data and significant outliers, high leverage points, or highly influential points, I confirmed no tolerance values greater than 0.1. and studentized deleted residuals greater than ±3 standard deviations. I also confirmed that no leverage values were greater than 0.2 and Cook's distance value above 1. Also confirmed the assumption of normality by visual inspection of a Q-Q Plot (Laerd statistics, 2015). I determined that all assumptions were met. Detailed analysis is provided in the exhibits (Appendix C).

As shown in Table 25 below, the *p*-value = .323 for the dependent variable (likely to obtain medication from Doctors or patient assistance programs) means *p* greater than .05. An indication that the multiple regression model did not statistically significantly predict the likelihood of obtaining medication from Doctors or patient assistance programs. It can also be deduced that none of the independent variables in the model (Health insurance status, Income, Gender, Monthly number of prescribed medications, Race, Age, Education, Monthly average prescription drug OOP expenses) did statistically significantly contribute to the model prediction of likelihood to obtain medication from Doctors or patient assistance programs, $F(8, 355) = 1.160$, $p < .05$.

Table 25

Multiple linear Regression Results: Model fit Anova[a] for Dependent Variable – Obtain Free Samples From Doctors or Patient Assistance Programs

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	6.188	8	.773	1.160	.323[b]
	Residual	236.678	355	.667		
	Total	242.865	363			

a. Dependent Variable: Likelihood of Obtaining free samples from doctors or patient assistance programs if all medication costs cannot be met
b. Predictors: (Constant), Independent Variables: Health insurance status, Monthly number of prescribed medications, Monthly average OOP expenses, Co-variables: Income, Education, Race, Gender, Age.

The multiple regression results, as shown in Table 26 below, indicated that the intercept is statistically significant at .000 (i.e., $p < .0005$), meaning that it is different from 0 (zero) (Laerd Statistics, 2015). However, the slope coefficients "B" column of Table (25) shows that the monthly number of prescribed medication = -.069 and monthly OOP expenses = 0.027. The slope coefficient was negative (monthly number of prescribed medication). An indication that an increase in the monthly number of prescribed medication (measured in numbers of prescribed medication) would have been associated with a decrease in the likelihood of obtaining a free sample from Doctors or patient assistance programs. Also, the slope coefficients are positive for an increase in monthly OOP expenses (measured in U.S.$) would have been associated with an increase in the likelihood of obtaining free samples from Doctors or patient assistance programs. However, the *p*-value is .137, 95% CI [-0.16, 0.02] for a monthly number of prescribed medication and monthly OOP expenses variables, $p = .591$, 95% CI [-0.071, 0.124], suggesting that the slope coefficient is not statistically significant; that is, no linear relationship when the slope coefficient is not different to 0 (zero) in the population (Laerd Statistics, 2015).

However, health insurance status is a categorical variable. The slope coefficient's value represents the dependent variable between the two categories of the variable. The two categories of the Insurance status variable are coded as "1" = "Yes" having health insurance and "2" = "No" having no health insurance. I compared the two categories to the category with a value of " 2". So, in this case, comparing having no health insurance "2" to having health insurance "1".The value of the slope coefficient is negative, -0.236, which means that predicted likelihood for having no health insurance is far greater than that of having health insurance to obtain a free sample from Doctors or patients assistance programs. Also, the *p*-value is .329 (i.e., $p > .05$, *p* is greater than .05), 95% CI [-0.71, 0.24]. Based on these values, the slope coefficient is not statistically significant ($p > .05$); that is, the slope coefficient is not different from 0 (zero) in the population (i.e., there is no linear relationship) (Laerd Statistics, 2017).

Overall, the multiple regression model did not statistically significantly predict the likelihood of obtaining free samples from doctors or patient assistance programs, $F(3, 355) = 1.160$, $p < .05$. The regression coefficients and standard errors (Table 26 below) adj. $R^2 = .004$, $R^2 =.025$, i.e., the R^2 for the overall model was 2.5% with an adjusted R^2 of .04%, a low size effect according to Cohen (1988). However, none of the variables added statistically significantly to the prediction, $p < .05$ with the prediction of obtaining free samples from doctors or patient assistance programs model in T2D adults controlling for demographics (Race, Age, Gender) and socioeconomic (Income, Education) variables. A suggestion that other factors need to be considered. Based on this result, I accepted the null hypothesis because none of the independent variables of interest contributed at a statistically significant level when all variables were included in the model. However, the model fit using the total variation explained (R^2 and adjusted R^2); the R^2 for the overall model (adjusted R^2 .004) is a low size effect, according to Cohen (1988).

Table 26

Multiple Regression Results for the Likelihood to Obtain Free Samples From Doctors or Patient Assistance Programs if all Medication Costs Cannot Be Met

Obtain free samples from Doctors or patient assistance program	B	95% CI for B		SE B	β	Adjusted R-squared	R-squared
		LL	UL				
Model						0.004	.025
Constant	4.75***	3.71	5.79	.53			
Monthly number of prescribed medications	-.07	-.16	.02	.05	-.09		
Monthly average prescription drug out-of-pocket (OOP) expenses	.03	-.07	.12	.05	.03		
Health insurance status	-.24	-.71	.24	.24	-.05		
Gender	.11	-.07	.28	.09	.06		
Race	.14	-.06	.33	.10	-.08		
Education	-.09	-.23	.06	.07	-.07		
Income	-.06	-.18	.07	.06	-.05		
Age	.05	-.15	.05	.05	-.06		

Note. Model = “Enter” method in SPSS statistics; B = unstandardized regression coefficients; CI = confidence interval; LL = lower limit; UL = upper limit; SE B = standard error of coefficients; β = standardized coefficient.

* $p < .05$, ** $p < .01$, *** $p < .001$

Research Question 4d - A Multiple regression statistics were run to predict the dependent variable (odds of reporting Spilt pills or changing the dosage frequency, survey question 13 (4) composite score) from the independent variables (insurance status, monthly OOP expenses, the monthly number of prescribed medication) among T2D adults controlling for demographics (Race, Age, Gender) and socioeconomic (Income, Education) variables. The assumption of linearity was assessed through visual inspection of the partial regression plots and a plot of studentized residuals against the predicted values. I also assessed the independence of residual assumption by checking the Durbin-Watson statistic value of the analysis, 1.952. While a value of approximately 2 indicates no correlation between residuals (Laerd statistics, 2017), I accepted that the assumption is met. The assumption of homoscedasticity of residuals was confirmed by visual inspection of a plot of studentized residuals versus unstandardized predicted values. Assessing the assumptions for multicollinearity of data and significant outliers, high leverage points, or highly influential points, I confirmed no tolerance values greater than 0.1. and studentized deleted residuals greater than ±3 standard deviations. I also confirmed that no leverage values were greater than 0.2 and Cook's distance value above 1. Also confirmed the assumption of normality by visual inspection of a Q-Q Plot (Laerd Statistics, 2015). I determined that all assumptions were met. Detailed analysis is provided in the exhibits (Appendix C).

As shown in Table 27 below, the *p*-value = .000 for the dependent variable (likely to obtain medication from Doctors or patient assistance programs) means $p < .001$. An indication that the multiple regression model statistically significantly predicts the likelihood of split pills or changing dosage frequency. I deduced that all the independent variables in the model (health insurance status, income, gender, monthly number of prescribed medications, race, age, education, monthly average prescription OOP expenses) did statistically significantly predict likely to split pills or change dosage frequency, $F(8, 355) = 4.704$, $p < .001$.

Table 27

Multiple Linear Regression Results: Model fit Anova[a] for Dependent Variable – Split Pills or Change the Dosage Frequency

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	37.628	8	4.704	5.453	.000[b]
	Residual	306.196	355	.863		
	Total	343.824	363			

a. Dependent Variable: Likelihood of Split pills or changing the dosage frequency if all medication costs cannot be met
b. Predictors: (Constant), Independent variables: Health insurance status, Monthly number of prescribed medications, Monthly average OOP expenses, Co-variables: income, education, race, gender, age.

As shown in Table 28 below, the intercept is statistically significant at .000 (i.e., $p < .0005$), meaning that it is different from 0 (zero) (Laerd Statistics, 2017). However, the slope coefficients "B" column Table 27, for the monthly number of prescribed medication = -.14 and monthly OOP expenses = -.10. The slope coefficient had been negative; an increase in the monthly number of prescribed medications (measured in numbers value) and monthly OOP expenses (measured in U.S.$) can decrease the likelihood of splitting pills or changing dosage frequency in contrast to the reasoned action theory prediction. Also, the *p*-value is .006, 95% CI [-0.25, -0.04] for a monthly number of prescribed medication and monthly OOP expenses, $p = .030$, 95% CI [0.233, -.012]. I determined that the slope coefficient is statistically significant. There is a linear relationship.

However, health insurance status is a categorical variable. The slope coefficient's value represents the dependent variable between the two categories of the variable. The two categories of the Insurance status variable are coded as "1" = "Yes" having health insurance and "2" = "No" having no health insurance. The comparison between the two categories is to the category with a value of " 2". So, in this case, comparing having no health insurance "2" to having health insurance "1".The value of slope coefficient is negative, -0.103, which means that predicted likelihood for having no health insurance is far greater than that of having health insurance to split pills or change dosage frequency. Also, the *p*-value is .707 (i.e., $p > .05$, p is greater than .05), 95% CI [-0.64 , 0.44]. I determine that the slope coefficient is not statistically significant ($p <.05$); that is, the slope coefficient is not different from 0 (zero) in the population (Laerd Statistics, 2017).

The multiple regression model statistically significantly predicts the likelihood of split pills or changing dosage frequency, $F(3, 355) = 4.704$, $p < .001$. The regression coefficients and standard errors, Table (27 below) adj. $R^2 = .089$, $R^2 =.104$, i.e., the R^2 for the overall model was 8.9% with an adjusted R^2 of 10%, a low size effect according to Cohen (1988). However, four variables added statistically significant to the prediction, $p < .05$. The variable monthly numbers of prescribed medication (B = -14, p = < .05, 95% CI [-0.24, -0.10]) and monthly OOP expenses (B = -.12, p = < .05, 95% CI [0.233, -.012] contributed at statistically significant level with the prediction of split pills or change dosage frequency in T2D adults controlling for demographics (Race, Age, Gender) and socioeconomic (Income, Education) variables. Based on this result, I rejected the null hypothesis because one or more independent variables contributed at a statistically significant level when all variables were included in the model. However, the model fit using the total variation explained (R^2 and adjusted R^2) for the overall model with an adjusted R^2 of .089 is a low size effect, according to Cohen (1988). Also, the regression model coefficient's negative effect indicates that the data may be inconsistent with the reasoned action approach model prediction.

Table 28

Multiple Regression Results for the Likelihood to Split Pills or Change Dosage Frequency if Medication Cost Cannot Be Met

Split pills or change dosage frequency	B	95% CI for B		SE B	β	Adjusted R-squared	R-squared
		LL	UL				
Model						0.089***	.109
Constant	4.16***	2.97	5.35	.60			
Monthly number of prescribed medications	-.14**	-.25	-.04	.05	-.15**		
Monthly average prescription drug out-of-pocket (OOP) expenses	-.12*	-.23	-.01	.06	-.13*		
Health insurance status	-.10	-.64	.43	.27	-.02		
Gender	-.09	-.29	.19	.10	-.04		
Race	.34**	.12	.56	.11	.16**		
Education	-.02	-.18	.14	.08	-.01		
Income	.07	-.07	.21	.07	.06		
Age	.16**	.05	.27	.06	.15 **		

Note. Model = "Enter" method in SPSS statistics; B = unstandardized regression coefficients; CI = confidence interval; LL = lower limit; UL = upper limit; SE B = standard error of coefficients; β = standardized coefficient.

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

Summary and Transition

Overall, to answer all research questions in this study, logistic regression statistics were run using SPSS version 27.0. to analyze the data set obtained from a survey questionnaire response from the study participants. Research questions (RQ1a -3d) using binomial logistics regression statistics measured or predicted what was used or not used, i.e., a dichotomous dependent variable (response to survey question 12 of the questionnaire, appendix 1). Research questions 4a-d measured or predicted what participants were likely to do (intention, response to survey question 13) using a multiple logistics regression model. All the research questions test the significance of the association between the study's independent variable of interest (monthly OOP expenses, monthly number of prescribed medications, insurance status) either independently (RQ1a-3d) or collectively (RQ4a-d) and each dependent variable (purchase medication over the internet, purchase medication from other countries, obtain free samples from Doctors or patient assistance programs and split pills or change dosage frequency), while controlling for demographics (race, age, gender) and socioeconomic (income, education) variables.

RQ1a-d results suggested that the increased monthly OOP expenses are not statistically significant or associated with the reduced odds of purchasing medication over the internet and not statistically associated with increased odds of obtaining a free sample from the doctor or patient assistance program. An indication that I could not reject the null hypotheses H_o1a and H_o1c. Also, the results suggested that the increased monthly OOP expenses are significantly associated with reduced odds of purchasing medication from other countries. An increase in monthly OOP expenses is significantly associated with an increased odds of splitting pills or changing dosage frequency among adults with T2D, which indicated that I could not reject the alternate hypotheses H_l1b and H_l1d.

However, while the model standard error ($adjR^2$) is considered a lower size effect, the negative coefficient effect contradicts the direction predicted in the reasoned action model for DV purchasing medication from other countries and purchasing medication over the internet from higher OOP expenses.

RQ2a-d results indicated that increasing the monthly number of prescribed medications is not significantly associated with a reduced odds of purchasing medication over the internet strategy and is not significantly associated with an increased odds of obtaining free samples from a doctor or patient assistance program. An observation that I could not reject the null hypotheses H_o2a and H_o2c. The increased monthly number of prescribed medications is significantly associated with reduced odds of purchasing medication from other countries and increased odds of splitting pills or changing dosage frequency. An indication that I could accept the alternate hypotheses H_l2b and H_l2d. However, while the model standard error ($adjR^2$) is considered a lower size effect, the negative coefficient effect contradicts the direction predicted in the reasoned action model for DV purchasing medication from other countries and purchasing medication over the internet strategy from increasing monthly number of prescribed medications.

RQ3a-d results suggested that health insurance status was significantly associated with the odds of reporting purchasing medication over the internet, indicating that I could reject the null hypothesis H_o3a. However, the results revealed that health insurance status was not significantly associated with the odds of reporting purchasing medication from other countries, not significantly associated with the odds of obtaining a free sample from Doctors or patient assistance programs, and not significantly associated with the odds of reporting split pills or change dosage frequency. An indication that I could accept the null hypotheses H_o3b, H_o3c, and H_o3d accordingly. However, while the model standard error ($adjR^2$) is considered a lower size effect, the negative coefficient effect contradicts the direction predicted in the reasoned action model for DV split pills or changing dosage frequency, purchasing medication from other countries, and obtaining a free sample from doctors or patient assistance programs strategy from increasing monthly number of prescribed medications.

RQ4a result indicated that I could not reject the null hypothesis H_o4a. The multiple regression model did not statistically significantly predict the likelihood of purchasing medication over the internet, $F(3, 355) = 1.128$, $p > .05$, adj. $R^2 = .003$, $R^2 =.025$. However, all the assumption testing was met only health insurance status variables added statistically significantly to the prediction, $p < .05$. The result should be treated with caution, while the low measured standard error effect (adj. $R^2 = .003$) and the coefficient effect and direction may influence reasoned action approach model prediction.

RQ4b result indicated that I could accept the alternative hypothesis H_l4b. The multiple regression model statistically significantly predicted the likelihood of purchasing medication from other countries, $F(3, 355) = 2.430$, $p < .05$, adj. $R^2 = .031$, $R^2 =.052$. However, while the assumption testing was met, none of the variables added statistically significantly to the prediction, $p < .05$. the results should be treated with caution, while the low measured standard error effect (adj. $R^2 = .031$) and the coefficient effect and direction may have influence reasoned action approach model prediction.

RQ4c result indicated that I could not reject the null hypothesis H_o4c. The multiple regression model did not statistically significantly predict the likelihood of obtaining free samples from doctors or patient assistance programs, $F(3, 355) = 1.160$, $p < .05$, adj. $R^2 = .004$, $R^2 = .025$. However, while the assumption testing was met, none of the variables added statistically significantly to the prediction, $p < .05$. the results should be treated with caution, while the low measured standard error effect (adj. $R^2 = .004$) and the coefficient effect and direction may influence reasoned action approach model prediction.

RQ4d results revealed that I could accept the alternative hypothesis H_l4d. The multiple regression model significantly predicted the likelihood of split pills or changing dosage frequency, $F(3, 355) = 4.704$, $p < .001$, adj. $R^2 = .089$, $R^2 = .109$. However, while all the assumption testing was met, monthly numbers of prescribed medication ($p < .01$), the monthly average of OOP expenses ($p < .05$), Race ($p < .01$),) Age ($p < .01$) variables were added statistically significantly to the prediction, the results should be treated with caution. At the same time, the low effect (adj.$R^2 = .089$) and the coefficient effect and direction may influence reasoned action approach model prediction.

The next chapter will discuss the interpretation of these findings in the extant literature and the theoretical framework that guided this study. The limitation of the study execution for generalizability, validity, and reliability will also be discussed. Finally, the recommendation for future research and implications of the study for positive social change is also described and the conclusion.

Chapter 5: Discussion, Conclusions, and Recommendations

Introduction

The purpose of this quantitative cross-sectional survey study was to investigate the association between T2D adult patients' self-reported OOP expenses, numbers of prescribed medication, insurance status, and the use of cost-saving strategies that include obtaining free samples from physicians or patient assistance programs, splitting pills, or changing dosage frequency, purchasing medication from other countries, and purchasing from the internet. According to the ADA (2018), adults diagnosed with T2D take at least one or more prescribed medications to manage their chronic illness. Most adults reported financial burden due to prescription medication OOP expenses for privately insured, underinsured, and uninsured adults diagnosed with T2D (ADA, 2018; Cohen & Cha, 2019) that impact medication regimen compliance (Goldsmith et al., 2017).

In this study, the research questions were developed to examine the association between the independent variables of interest and four separately measured dependent variables (purchased medication over the internet; purchased medication from other countries; obtained free medication from doctors or patient assistance programs; split pills or changed dosage frequency) define as alternative medication cost-savings strategies. First, a binomial logistics regression model was used to examine the association of individuals' independent variables of interest (monthly OOP expenses, monthly numbers of prescribed medications, health insurance status) and the likelihood of using each alternative medication cost-saving strategy (survey question 12 checklist that measured actual used, Appendix A). Second, a multiple logistics regression model was used to examine all three independent variables of interest simultaneously and predict the likelihood of using each alternative medication cost-saving strategy (survey question 13 (1) composite score that measured likely to use each strategy, Appendix A) among adults diagnosed with T2D in the United States.

These study findings showed that adults diagnosed with T2D and prescribed medications spent an average of $115 monthly OOP expenses on five or more monthly prescribed medications. Among those who reported health insurance status, 95% have one or more types of health insurance, and 3.4% have no insurance. The most widely used cost-savings strategy in the last 12 months was purchasing medication from other countries (36.2%) and purchasing medication over the internet (35.6%). Also, when all medication cannot be afforded, 35.1% were extremely likely to split pills or change dosage frequency, followed by purchasing medication from other countries (28.8%), and 27.7 % will be extremely likely to obtain free medications from doctors or patient assistance programs. The study findings revealed that increased monthly OOP expenses are associated with a reduction in purchasing medication from other countries and an increased likelihood of splitting pills or changing dosage frequency while purchasing medication over the internet and purchasing from other countries or obtaining free samples from the doctor or patient assistance program are not associated. Increased monthly number of prescribed medications is associated with increased likelihood of splitting pills or changing dosage frequency, or reduced likelihood of purchasing medication from other countries while purchasing medication over the internet and obtaining free samples from a doctor or patient assistance program are not associated.

Health insurance status is associated with an increased likelihood of purchasing medications over the internet and a reduced likelihood of obtaining free samples from the doctor or patient assistance programs, whereas purchasing medications from other countries, and splitting pills or changing dosage frequency strategies were not associated. The multivariate analysis significantly predicted that all the three independent variables are likely associated with purchasing medication from other countries and splitting pills or changing dosage frequency but could not significantly predict the likelihood of purchasing medication over the internet or obtaining free samples from doctors or patient assistance programs.

Interpretation of the Findings

Health insurance status and prescription medication costs have been predictive factors in using cost-savings strategies to manage costs among adults diagnosed with T2D (Cohen & Cha, 2019). These study findings revealed that having health insurance is 12 times more likely than not having health insurance to purchase medications over the internet. At the same time, 95% of all respondents in this study reported having one or more health insurance types; the positively significant health insurance status may have indicated that this influence only held for those with health insurance coverage and purchase medication over the internet, implying no different health insurance status for those who did not use the strategies (Musich et al., 2015). In this study, the monthly OOP expenses and numbers of prescribed medications do not significantly affect the likelihood of purchasing medication over the internet. However, increasing OOP expenses and the monthly number of prescribed medications have a 16% reduced likelihood of purchasing medication over the internet. In the analysis, age and education significantly influenced the likelihood of purchasing medication over the internet in OOP expenses and the monthly number of prescribed medication variables. This study result shows that increasing age may have been associated with a 31% increase likelihood, while having a higher educational level may have been associated with a 29% increase likelihood of purchasing medication over the internet for OOP expenses variables. At the same time, age (30%) and education (90%) increase the likelihood of purchasing medication over the internet for a monthly number of prescribed medication variables. The study average age range for all participants ranged between 33 to 44 years, with an average of 4 years of college graduate educational level. These results support the findings that while higher OOP and being prescribed many medications may have reduced likelihood, those who purchase medication over the internet may have had cost management skills and expertise in accessing this source (Musich et al., 2015). These results compared favorably with other studies, which suggested that demographics, socioeconomic (covariables in this study) and health literacy, or lifestyle factors as such not considered in this study, may influence the use of cost-savings strategies (Hong et al., 2020; Musich et al., 2015).

When the increased prescribed medications would increase the financial burden to remain compliant with the medication regimen getting more medication is a predictive likelihood of using cost-saving strategies (Cohen & Villarroel, 2015; Musich et al., 2015). This study’s results showed that the increased monthly number of prescribed medications and OOP expenses is significantly associated with a 37% reduced likelihood of purchasing medication from other countries. At the same time, one covariable (race) contributed to the independent variable OOP expenses model prediction in reduced likelihood of purchasing medication from other countries. However, the significant effect resulting in reduced likelihood due to the increased number of monthly prescribed medications may be that other factors contributed to the effect. This result supports the findings that adults diagnosed with T2D and prescribed medication, which used the cost-savings strategy, may not probably report the unfortunate situation or other reasons for the usage (Cohen & Cha, 2019). These results compared favorably with other studies, which suggested that demographics, socioeconomic (covariables in this study) and health literacy, or lifestyle factors as such not considered in this study, may influence the use of purchasing medication from other countries as cost-savings strategies (Hong et al., 2020; Musich et al., 2015). However, in this study, being uninsured makes one twice more likely to purchase medication from other countries than someone who is insured. At the same time, health insurance status has no significant effect on the results. Although 95% of all respondents reported having one or more health insurance types, a small percentage (3.4%) reported not having health insurance. These results may be that the people who use this cost-saving strategy may have done so for reasons other than health insurance status (Cohen & Cha, 2019). This result is favorable compared to Hong et al.'s (2020) study findings that people who purchase medication from other countries depend largely on prescription medication access and affordability options than insurance status among T2D patients (Toulouse & Kodadek, 2016).

OOP expenses have been associated with prescription medication cost among adults with prescribed medication in using a cost-savings strategy (Cohen & Cha, 2019;

Musich et al., 2015). This study found no significant effect in predicting the likelihood of obtaining free samples from a doctor or patient assistance program increased monthly OOP expenses, resulting in 7% more likely. At the same time, increased monthly numbers of prescribed medications resulted in a 17% increase likelihood of obtaining free samples from a doctor or patient assistance program. The effect's insignificant may be that other factors were not a variable in the model (Laerd statistics, 2017). The insignificant results could be because of other factors. For example, some organizations or pharmacy stores offer a lower cost redeemed card that will be redeemed up to 80% on prescription drugs (Walmart, 2019). Physicians often recommend that uninsured patients get discount cards (Pallarito, 2018). However, in this study result, 20.7% of all participants (adults diagnosed with T2D) self-reported having obtained or being extremely likely (27.3%) to obtain free samples from doctors or patient assistance programs when asked about a cost-savings strategy that has been used or that they were likely to use to save on their prescription medication costs. These results were favorable compared to Cohen and Cha’s (2019) report that 26.3% of younger adults aged under 65 among those diagnosed with diabetes in the United States and prescribed two or more medication asked their physicians for lower-cost medication between 2017 and 2018. However, while there are no significant effects associated with health insurance status and the likelihood of obtaining a free sample from the doctor or patient assistance programs in this study, the result showed that those who reported having health insurance are more likely to use it than not having health insurance. Perhaps insurance status may not significantly affect obtaining a free sample from the doctor or patient assistance programs. In this study, 20.7% reported having obtained or extremely likely (27.3%) to obtain a free sample from their doctor or patient assistance program, while a small percentage (3.4%) of all respondents reported not having health insurance at all, and 95.1% reported having one or more health insurance coverage, with most reporting employer insurance (39%), Medicaid (26%) and Medicare prescription plan insurance (14%). This result supports the finding of this study. Although Cohen and Cha's study of adults diagnosed with T2D that used prescription medication in the United States between 2017 and 2018 found that 42.6% of adults below age 64 diagnosed with diabetes who reported having no health insurance will ask their doctor for low-cost prescription medication.

This study found that increasing monthly OOP expenses are significantly associated with a 64% increased likelihood of splitting pills or changing dosage frequency. At the same time, the results revealed that an increased monthly number of prescribed medications is associated with a 41% increased likelihood when all the variables do not contribute to the result significance. Among all participants, 7.4% self-reported splitting pills or changing dosage frequency, whereas 35.1% reported being extremely likely to use if all medication costs were not afforded. This result's significant effect may be that those who reported splitting pills or changing dosage frequency among adults diagnosed with diabetes to reduce prescription drug cost in this study may have been doing so for prescription medications' financial burdens (Cha & Cohen, 2019). This result is compared favorably with Cohen and Cha's (2019) findings that found 17.9 % of the younger adult and 7.2% of adults over 65 diagnosed with diabetes between 2017 and

2018 in the United States were more likely not to have taken their prescription as directed. Consistent with other studies, the habit of splitting pills or changing dosage frequency is more predictive when OOP expenses and the number of prescribed increase, resulting in medication nonadherence (Goldsmith et al., 2017; Guerard et al., 2018; Musich et al., 2015). While health insurance status is not significantly associated with splitting pills or changing dosage frequency, the likelihood of using the strategy is 3.7 times greater for those without health insurance than those with health insurance in this study.

Interestingly, the study results show that a small percentage (3.4%) of all respondents reported having no health insurance at all, and 95.1% reported having one or more health insurance types, with most reporting employer insurance (39%), Medicaid (26%), and Medicare prescription plan insurance (14%). The result supports the findings that split pills or change dosage frequency strategy is a common strategy likely to use among uninsured or underinsured (Musich et al., 2015). These findings are favorable compared to Cohen and Cha's (2019) study that found 35.7% of younger adults aged below 65 diagnosed with diabetes who lack health insurance coverage are more likely not to have taken their medication as prescribed than 17.8% of those on Medicaid, 14.0% of those with private insurance.

Similar to bivariate results, this study showed that the multivariate analysis that simultaneously examined all three independent variables of interest did not statistically significantly predict the likelihood of purchasing medication over the internet. But the model's prediction for health insurance status is statistically significant. At the same time, monthly OOP expenses and monthly numbers of prescribed medication did not significantly add to the model prediction statistically. However, the predicted likelihood of purchasing medication over the internet for having health insurance is three times more likely than having no health insurance. An increase in monthly OOP expenses and numbers of prescribed medications resulted in a 32% increase in the likelihood of purchasing medication over the internet. This result supports the finding that while higher OOP expenses and the number of prescribed medications encourage purchasing medication over the internet, those who utilized the strategy have access to health insurance. As in other studies, most people who purchase pharmaceuticals online did so for cost-consideration (Kennedy & Wilson, 2017), insurance status is associated with purchasing medication over the internet as a cost-reduction strategy for adults diagnosed with T2D and patients prescribed two or more medications who used cost-savings strategies to save on prescription drug costs (Cohen & Cha, 2019; Musich et al., 2015).

The study found that while the multiple regression model statistically predicted the likelihood of purchasing medication from other countries, none of the variables added statistically significant to the prediction. An indication that the low effect size of the variation explained in the model may be a factor (Laerd Statistics, 2017). However, the predicted likelihood of having no health insurance is 12 times greater than having health insurance for purchasing medication from other countries. It also predicted an increase in the monthly OOP expenses and numbers of prescribed medication resulting in a 10% reduction in the likelihood of purchasing medication from other countries among U.S. adults diagnosed with T2D. In contrast, the bivariate analysis revealed that an increased number of prescribed medications variables is significantly associated with a reduced likelihood of purchasing medication over the internet. These results support the findings that while uninsured or underinsured encourage purchasing medication from other countries, those who purchase medication from other countries may also have done it for other reasons and may not have reported the unfortunate situation (Hong et al., 2020). While this study did not consider border location or class of drug to estimate purchase from another country, past studies indicated that individuals or communities located around the border are likely to cross neighboring countries to purchase their prescribed medication due to high cost in the United States (Calvillo & Lal, 2003; de Guzman et al., 2007; García et al., 2015).

This study's multiple regression model analysis did not significantly predict the likelihood of obtaining free samples from doctors or patient assistance programs. Consistent with the bivariate result, none of the variables of interest added statistically significantly to the prediction in the analysis. However, the results show that an increase in the monthly number of prescribed medications resulted in a 7.4% reduction in the likelihood of obtaining a free sample from doctors or patient assistance programs. An increase in monthly OOP expenses would have been associated with a 37% increase in the likelihood of obtaining free samples from Doctors or patient assistance programs. While insurance status has no significant effect, having health insurance is three times more likely than having no health insurance to obtain a free sample from Doctors or patient assistance programs among U.S. adults diagnosed with T2D. The result supports the findings that, while higher OOP expenses encourage adults diagnosed with T2D to obtain free samples from Doctors or patient assistance programs, usage as a cost-saving strategy varies by the individual (Cohen & Cha, 2019; Musich et al., 2015). Accessing health insurance is an important factor in using the cost-savings strategy, as evidenced in this finding and other studies (Adepoju et al., 2019; KFF, 2019; Toulouse & Kodadek, 2016).

However, as in the bivariate analysis results, the multiple regression model statistically significantly predicts splitting pills or changing dosage frequency in this study. However, not all variables added statistically significantly to the model prediction. In the results, the model predicted that while increased monthly numbers of prescribed medication statistically significantly contributed to the reduction likelihood by 16%, an increase in monthly OOP expenses also contributed at a statistically significant level with a 14% reduction for the likelihood of splitting pill or changing dosage frequency. While health insurance status is not significant in the model prediction, participants who reported not having health insurance are nine times more likely to split pills or change dosage frequency than those with health insurance. These results support the bivariate analysis finding that being uninsured or underinsured is the primary reason among other prescription medication cost-related issues with adults diagnosed with T2D engaging in the use of split pills or change dosage frequency cost-savings strategy. In contrast, OOP expenses and being prescribed many medications reduced the likelihood of split pills or changing dosage frequency but were associated with using a cost-savings strategy in this study. This result is favorable to other studies that found prescription medication cost-related nonadherence issues or habits of splitting pills or delaying filling prescriptions among adults diagnosed with T2D (Cohen & Cha, 2019, Goldsmith et al., 2017; Nipp et al., 2016).

Interpretation of Findings (Theoretical Perspective)

The theory I used in this study is the reasoned action approach, which combines the theory of planned behavior (TPB) and the theory of reasoned action (TRA). The theory predicted behavior based on the human attitude, subjective norm, and perceived behavioral control towards intention. In this study, the construct “intention” to use a cost-savings strategy was employed for each dependent variable (survey question 13 (1) composite score of the survey questionnaire, Appendix A). Using a multiple regression model (analyze the association between multiple independent variables and one continuous dependent variable) to answer the “likelihood” of using each cost-savings strategy if participants cannot afford medication for diabetes condition. The response was measured on a “5” points Likert scale ranging from “1” extremely unlikely to “5”- extremely likely. The reasoned action approach uses a set of variables that account for important variance in a particular behavior (Fig. 1; Fishbein, 2008). Thus, in this study, the respondent’s self-reported response to the three independent variables of interest represent Attitude (ATT), Subjective norm (SN), and perceived behavioral control (PBC) construct of the reasoned action approach framework as described below:

(1) ATT - monthly OOP expenses (survey Question 11 asked participants to indicate monthly average prescription drug OOP expenses for diabetes prescription medication). Fishbein and Ajzen (2010) noted that the attitude toward behavior in question (in this study, utilization of alternative medication cost-saving strategy, survey

item Q13, Appendix A) could be an anticipated positive or negative consequence in the reasoned action model. All variable (significant predictors) measures in the reasoned action model were adapted from the self-reported items selected in the survey questions (Appendix A). According to Fishbein (2008), behavioral beliefs are often cost benefits or outcome expectancies for measuring attitude. Thus, in this study, participants were asked to rank or score ("1" highest to "5" Lowest) their monthly average prescription OOP expenses (Survey question 11, Appendix A) for their diabetes condition on a scale of 1-5 items. The score on a five items scale ratio, coded as follows: 1 = $481- above, 2 =$116 – 481, 3 = $115 – 110, 4 = $110 – 51, 5 = $50 – below, indicating "1" highest and "5" lowest, measure participants' attitudinal concern towards utilizing and intention to use cost-saving strategies to save money on their prescription medication. In this study, among all respondents, the self-reported responses on the monthly OOP expenses mean an average score of 2.85 (SD = 0.996) on a scale of 5 possible items, where "1" is coded highest, and "5" is coded lowest, indicating positive to a negative attitude towards the use of strategies (Fishbein & Ajzen, 2010). At the same time, the study logistic regression analysis findings revealed that increased monthly OOP expenses are associated with an increased likelihood of splitting pills or changing dosage frequency while purchasing medication over the internet and purchasing from other countries or obtaining free samples from the doctor or patient assistance program are not associated. Although, the question asked in this study to measure attitude might not suggest all the reasons or decisions involved in using a particular strategy but a significant predictor (Jian et al., 2016). Consistent with other studies, adults diagnosed with diabetes in the U.S. reported a willingness to use strategies to save costs due to higher OOP expenses (Cha & Cohen, 2019; Hong et al., 2020; Musich et al., 2015).

(2) The subjective norm (SN) is about whether an individual perceives social pressure and belief that others will or not perform the behavior (Fishbein & Ajzen, 2010). In this study, all the significant predictors in the reasoned action model were adapted from the self-reported items in the survey response as evidence suggested that the cost of purchasing more medication increases the need to use a cost-savings strategy to comply with medication regimen (Musich et al., 2015). Therefore, the value of subjective norm is an aggregate of the construct (Jian et al., 2016). The survey items in this study (survey question 8, Appendix A) asked participants to indicate how many medications, including those currently taking, and any new medications were prescribed for diabetes condition in the last month. The six items coded as "1" = 9 or more, "2" = 7 – 8, "3" = 5 – 6, "4" = 3 – 4, "5" = 1 – 2, "6" = none, indicating that score of "1" highest and "6" lowest provides insight to estimate individual participants belief or perceived social pressure to perform or not perform the behavior (Fishbein, 2008). Thus, this study measures the intention among adults diagnosed with T2D to use a cost-savings strategy to save on prescription medication. The scale ratio items used in this measure seem to parallel the measure of a subjective norm in Ajzen's (1991) study that asked participants with increased active commuting whether others would approve or disapprove intention to increase active commuting. However, among all respondents in this study, the self-reported response to monthly numbers of prescribed medication mean is 3.41 out of a possible 6 (SD =1.05; survey Q8, Appendix A). At the same time, this study result in a multiple regression

analysis indicated that an increase in the monthly number of prescribed medications is associated with an increased likelihood of splitting pills or changing dosage frequency or a reduced likelihood of purchasing medication from other countries while purchasing medication over the internet and obtaining free samples from a doctor or patient assistance program are not associated. This result supports the finding that using this scale to estimate the amount of medication prescribed for an adult diagnosed with T2D indicates an important variance in the perceived perception or behavior toward using medication cost-savings strategy or alternative medication sources to save cost and compliant with their medication regimen. This study's result is favorable compared to other studies suggesting that as purchasing more medication becomes a financial burden, increasing the number of prescribed medications or taking more medication is highly predictive of using a cost-savings strategy (Cha & Cohen, 2019; Musich et al., 2015) or medication non-compliance (Goldsmith et al., 2017).

(3) In this study, the participant's self-reported insurance status variable was used to measure perceived behavioral control (PBC) that moderates the effects of ATT (OOP expenses) and SNs (number of prescribed medications) to predict actual BI towards a behavior (Karimy et al., 2019; La Barbera & Ajzen, 2020). For example, the health insurance status variable has been reported as a PBC in a study that used the theory of planned behavior to determine the intention to self-medicate among women (Karimy et al., 2019). In this study, I found that participants' responses to likely use strategy to afford the cost of all prescribed medications (survey Q13 composite score, Appendix A) for T2D condition that measures the intention to use each cost-savings strategy score an

average of 3.74 (SD = 0.98) of the five maximum scores likely to purchase medication over the internet; and 3.75 (SD 1.08) scores out of five for equally likely to purchase medication from other countries. A multiple regression model analysis revealed that health insurance status significantly affects the predicted likelihood of purchasing medication over the internet. The variable did not significantly affect the predicted likelihood of purchasing medication from another country. At the same time, the predicted likelihood of having no health insurance is 12 times greater than having health insurance for purchasing medication from other countries, and purchasing medication over the internet for those with health insurance is three times greater than having no health insurance. As in these result findings and other studies, this difference could be that characteristics associated with the individual purchase of medication outside the United States and over the internet may be attributed to the prevalence of online pharmacies, which can be done at any location (Hong et al., 2020; Kennedy & Wilson, 2017). However, this study's findings showed that 96.6% of the participants self-reported having one or more health insurance, and 3.4% with no health insurance. While most participants reported being prescribed one or more medications, have used or are likely to use a cost savings strategy as in this study and another study confirmed the belief that having medical health insurance controls the cost of healthcare service (Karimy et al., 2019). Although, purchasing medication over the internet or in other countries may also be a factor in health insurance status, among other reasons (Kennedy & Wilson, 2017). An assertion also supported in similar studies is that health insurance status is an important factor in using alternative medication cost-savings strategies (Cohen & Cha, 2019; Musich et al., 2015).

Interestingly, in these study findings, when the dependent variables were measured separately employing the same questionnaire to measure intention (survey question 13 composite score, Appendix A), among all participants on a scale of five, the mean score for DV, Purchase medication over the internet, 3.74 (SD 0.98) and 3.75 (SD 1.08) for DV, Purchase medication from other countries. The average score for DV to obtain a free sample from Doctors or patient assistance programs was 3.97 (SD 0.85); and 4.0 (SD 0.98) for DV, split pills, or change dosage frequency. The higher scores on the variables measured in this study result support the findings that behavioral beliefs and outcomes influence intention and behavior (Fishbein, 2008; Fishbein & Ajzen, 2010; Jian et al., 2016; La Barbera & Ajzen, 2020). Therefore, the reasoned action approach used in this study may have helped explain the intention predictions for using each cost-savings strategy. However, it is worth noting that this study's finding in a multiple logistics regression model indicated no significant statistical effect in the model predicting the likelihood of obtaining free samples from a doctor or patient assistance program and positively predicted purchasing medication from other countries from the constructs composite score. At the same time, none of the variables contributed to the model prediction in some models. However, increasing monthly OOP expenses resulted in 7% more likely to obtain free samples from a doctor or patient assistance program. The monthly numbers of prescribed medication resulted in a 17% increase in the likelihood of obtaining free samples from a doctor or patient assistance program. This study results also showed that the increased monthly number of prescribed medications and higher OOP expenses are significantly associated with a 37% reduction in the likelihood of purchasing medication from other countries. Also, in the same model, health insurance status has no significant effect on the results, but having health insurance increases the likelihood. These results support the findings that the coefficient was in the direction predicted. Thus, the negative coefficient effect on some variables of interest in this study contradicts the reasoned action theory that behavior could be explained by attitude towards the cost of prescription medication (higher OOP expenses), perception or subjective norm, societal approval or disapproval (the number of prescribed medication) towards intention to use strategy; while attitudes and subjective norms are moderated by people's perceived behavioral control (health insurance status) toward intention (Karimy et al., 2019).

Consequently, in this study, the model fit using the total variation explained (R^2 and adjusted R^2); the R^2 for the overall model ranged from .025 to .109, with an adjusted R^2 ranging from .003 to .289, a low size effect according to Cohen (1988) may influence the predictions. However, the data were consistent with the model, given that the coefficients were in the direction predicted. At the same time, the reasoned action approach prediction may not be consistent with the data in some models with a negative coefficient effect, indicating that the mechanism may not be consistent with the theory prediction (Lindsey, 2017). Consistent with the findings and other studies, the independent variable of interest in this study may not be the only factor that influences the risk of using alternative medication cost-savings strategy, while the belief that prescription medication constitutes a higher financial burden may be associated with medication non-compliance (Cohen & Cha, 2019; Goldsmith et al., 2017; Hong et al., 2020; Musich et al., 2015).

Limitations of the Study

The mTurk population sample's nonprobability nature was of concern because it might not accurately represent the actual T2D population in the U.S. (Chandler & Shapiro, 2016). For example, the study may have oversampled those with or without insurance and more male respondents than females. The study controlled for demographics and socioeconomic status may affect the generalizability of the finding from this population sample (Solon et al., 2015). At the same time, the completely reliant on self-reported information may also affect the result (Jian et al., 2016). Also, respondents (mTurk members) may be at risk of survey fatigue because of other tasks that earn more money due to the nature of the survey administration (Amazon Turk; Adepoju et al., 2019). The pressure on mTurk members to answer without giving much thought to the survey questions may also limit the generalizability of the findings (Adepoju et al., 2019). The response to the variable of interest that assessed the construct of the theoretical approach may not accurately describe all the predictors associated with using alternative cost-savings strategies in this study.

Recommendations

Other studies have reported the impact of different types of health insurance coverage (Adepoju et al., 2019). However, they do not relate to alternative medication use cost-savings strategies, while some studies reported the likelihood of participants' health insurance plans using alternative medication sources or therapy (Cohen & Cha, 2019; Cohen &Villarroel, 2015; Kennedy &Wilson, 2017; Musich et al., 2015). In this study, I found that almost 97% of respondents have one or more types of health insurance coverage and reported the likelihood or use of cost-savings strategies, which could add to the predictors in the usage of strategies considered. However, the scope of this study did not address or assess the impact of health coverage plans that influence participants' use of alternative medication cost-savings strategies among adults diagnosed with T2D in the United States. Based on the result presented in this study, an additional study would be recommended to investigate the relationship or role of the type of medical insurance coverage plan options and OOP expenses and amount of prescribed medication in the usage of the alternative medication cost-savings strategies among U.S. residents.

Implications

Implications for Social Change

This study's positive social change revelation is that people with T2D use a cost-savings strategy to manage their prescription drug costs and maintain medication regimens. Therefore, suggested that prescription medication OOP expenses, numbers of prescribed medications, and patient's health insurance status are important factors associated with the use of alternative medication cost savings strategies among adults diagnosed with T2D. Thus, the decision to use an alternative strategy may be a source for many patients to access affordable, consistent drugs to manage medication compliance for their health condition. Therefore, understanding the prevalence and association of the predictors and alternative prescription medication cost-saving strategies, mostly unreported sources in CMS claim data, investigated in this study will guide the policy effort to address prescription medication financial burden and help health service users to access prescribed medication, especially those diagnosed with T2D and prescribed many medications with or without health insurance.

Implications for Theory

The reasoned action approach that guided this study discussion explains better the extent to which the attitude toward behavior and subjective norm moderated by perceived behavioral control (PBC) influence an individual behavioral intention or change behavior to use alternative medication cost-savings strategy (Jian et al., 2016; Karimy et al., 2019; La Barbera & Ajzen, 2020). Although, some of the findings in this study may have contradicted the theoretical prediction of intention and behavior change among individuals diagnosed with T2D. Nevertheless, the reasoned action approach descriptively explains these study results on how patients' self-reported monthly OOP expenses, monthly numbers of prescribed medication, and insurance status has influenced their use of specific CMS unreported source of cost-savings strategies to cope with medication regimen. For example, health insurance status is believed to link with health behavior and intention to self-medicate among women (Karimy et al., 2019). This study's reasoned action approach prediction confirmed the association between the independent variables of interest (monthly OOP expenses, monthly numbers of prescribed medication, and insurance status) and medication alternative cost-savings strategy. Therefore, contributed to the existing theory in health service and behavioral practices.

Implication for Practice

These study findings suggest that medication cost-related access, including patient's health insurance status, OOP expenses, and numbers of prescribed medications among adults diagnosed with T2D, which use health services, requires different approaches. By identifying the predictors for certain alternative medication cost-savings strategies, these study findings help reduce higher healthcare costs for adults diagnosed with T2D and contribute to advanced practice in healthcare services. However, the study findings suggested that providers of health services understand the legitimacy of certain unreported (untrackable) sources of alternative medication cost-savings strategy usage while mitigating the risk of medication non-compliance for the consumers and healthcare services users'. The practitioners, including health and behavioral services, could use these findings by identifying opportunities to improve healthcare service access to prescription medication and shape policies to lower prescription medication costs to benefit healthcare consumers.

Conclusion

Health insurance status is significantly associated with increased purchasing of medication over the internet to save prescription medication costs. An increase in monthly amounts of prescribed medication and OOP expenses are significantly associated with reducing purchasing medication from other countries, increasing splitting pills, or changing dosage frequency. In contrast, while none of the interest variables positively predicted obtaining free samples from doctors or patient assistance programs, this study found that increased OOP expenses and the monthly number of prescribed medications increased the usage and health insurance status reduced the use as a cost-savings strategy. These findings further demonstrated that using alternative medication cost-savings strategies is for many reasons of prescription drug financial burden to comply with medication regimen among U.S. residents adults diagnosed with T2D.

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Appendix A: IRB Approval Document and the Study Survey Questions

Draft of the survey link or invitation (amazon crowdsourcing Mechanical Turk (mturk.com) and informed consent on the Qualtrics survey platform (Qualtric.com) before taking the survey.

mturk.com - Survey Distribution, Workers Invitation letter – Survey link updated 06.25.21

Create | Requester | Amazon Mechanical Turk (mturk.com)

Project: Oduwaye Ph.D. Dissertation survey link invitation (Not displayed to workers)

Title: Answer a survey about cost and use of prescription drug alternative cost-savings Strategy

Description: The survey concerns your opinions about the financial burden and usage of one or more alternative cost-saving sources to comply with your medication regimen.

Keywords: Type2- diabetes (T2D), prescription drug, cost-savings strategy, financial burden, out-of-pocket expenses, health insurance status, medication compliance

Displayed to workers:

Answer a survey about cost and use of prescription drug alternative cost-savings Strategy

Requester: Solomon Oduwaye

Reward: $1.00 per task Tasks available: 0 Duration: 15 Minutes

Qualifications Required: Location is U.S.

Survey Link instructions: You are invited to participate in a research study about alternative cost-savings strategies used to save on a prescribed medication among adults with Type-2 diabetes. The researcher is inviting 18 years of age or older, US residents who self-report being diagnosed with type 2-diabetes and used any prescribed medication in the last twelve months to be in the study. Select the link below to complete the survey. At the end of the survey, you will receive a code to paste into the box below to receive credit for taking the survey.

Make sure to leave this window open as you complete the survey. When you are finished, you will return to this page to paste the code into the box.

Template note for Requesters - To verify that Workers actually complete your survey, require each Worker to enter a **unique** survey completion code to your HIT. Consult with your survey service provider on how to generate this code at the end of your survey.

Survey link:	http://example.com/survey345.html

Provide the survey code here:

Submit

qualtrics.com - survey design/ and informed consent.

https://survey.sjc1.qualtrics.com/jfe/preview/SV_0Hs5aQ4xZTKDBga?Q_CHL=preview&Q_SurveyVersionID=current

Welcome to the research study! Predictors of Medication Alternative Cost-Saving Strategies among Adults with Type2-Diabetes.

Survey Questions
About You

1. What is your age?

☐ 18 to 24

☐ 25 to 34

☐ 35 to 44

☐ 45 to 54

☐ 55 to 64

☐ 65 to 69

☐ 70 and above

2. Are you male or female?

☐ Male

☐ Female

3. What is the highest grade or level of school that you have completed?

☐ 8th grade or less

☐ Some high school, but did not graduate

☐ High school graduate or GED

☐ Some college or 2-year degree

☐ 4-year college graduate

☐ More than 4-year college degree

4. What is your race?

□ White

□ Black or African American

□ Latino ethnic background

5. What is your income?

□ $76,000 - above

□ $51,000-75,999

□ $25,000-50,999

□ $24,000- below

6. Have you ever been told by a doctor or other professional that you had Type 2 diabetes?

□ Yes

□ No

7. In the last 12 months, did you take any prescribed medication?

□ Yes

□ No

PART II (Section 2 Questions relevant to the study)

8. In the last month, how many medications, including those you were already taking, and any new medications prescribed for your diabetes?

□ 9 or more
□ 7 - 8
□ 5 - 6
□ 3 - 4
□ 1 – 2
□ None

9. Do you have health insurance?

☐ Yes

☐ No

10. Please mark the type of health insurance you have.

☐ Medicaid

☐ Veteran's benefits

☐ Employer Insurance

☐ Union or Retire health coverage

☐ Medicare prescription plan

☐ Affordable Care Act (ACA) or Medicaid Expansion

☐ Other private insurance/not sure

11. What are your monthly average prescription drug out-of-pocket (OOP) expenses for your diabetes condition?

☐ $481- above

☐ $116 - 481

☐ $115 – 110

☐ $110 - 51.

☐ $50 - below.

12. In the last 12 months, did you use any of the following to save money on your prescription medication? (Check all that apply)

☐ Purchase medication over the internet
☐ Purchase medication from other countries
☐ Obtain free samples from doctors or patient assistance programs
☐ Split pills or changed the dosage frequency

13. If you cannot afford all the medications for your diabetes, what are you likely to do?

1. Purchase medication over the internet

☐ 1 Extremely unlikely ☐ 2 Unlikely ☐ 3 Neutral ☐ 4 likely ☐ 5 Extremely likely

2. Purchase medication from other countries

☐ 1 Extremely unlikely ☐ 2 Unlikely ☐ 3 Neutral ☐ 4 likely ☐ 5 Extremely likely

3. Obtain free samples from doctors or patient assistance programs

☐ 1 Extremely unlikely ☐ 2 Unlikely ☐ 3 Neutral ☐ 4 likely ☐ 5 Extremely likely

4. Split pills or changed the dosage frequency

☐ 1 Extremely unlikely ☐ 2 Unlikely ☐ 3 Neutral ☐ 4 likely ☐ 5 Extremely likely

End survey. Thank you.

Appendix B: Permission to Reuse Figure (1)

RP-5425 republish and modify figure for use in my dissertation

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CM

Craig Myles <permissions@sagepub.com>
Thu 5/27/2021 4:54 PM

To:

- Olaseni Oduwaye

Reply above this line.

Craig Myles commented:

Dear Olaseni Solomon Oduwaye,

Thank you for your ticket. I am pleased to report we can grant your request to reuse Figure 1 from "A Reasoned Action Approach to Health Promotion" without a fee as part of your dissertation.

Permission is granted for the life of the dissertation on a non-exclusive basis, in the English language, throughout the world in all formats provided full citation is made to the original SAGE publication. Permission does not include any third-party material found within the work.

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If you have any questions, or if we may be of further assistance, please let us know.

Best regards,

Craig Myles

Appendix C: Research Question 4a-d - Multiple Linear Regression Assumptions

Research questions, 4a-d were developed to examine the association between all three independent variables of interest simultaneously and the likelihood of using each alternative medication cost-saving strategy (survey question 13 (1) composite score that measured likely to use each strategy, Appendix A) among adults diagnosed with T2D in the U.S.

Assumption testing RQ4a - Assumptions were run using SPSS version 27 to assess how the data fit the model predicting the likelihood of Purchasing medication over the internet in multiple regression analysis:

1. Assumption of Independence of observations – I assessed independently of residuals by Durbin-Watson statistics. The Durbin-Watson (shown in Table 5 below) is 1.854. According to Laerd Statistics (2015), the Durbin-Watson statistic value can range from 0 to 4, but a value of approximately 2 indicates no correlation between residuals. In this analysis, I accepted independent errors (residual).

Table C 1

Descriptive Statistics: Multiple Regression Model Summary Table for the Dependent Variable Likelihood to Purchase Medication Over the Internet (b)

Model	R	R square	Adjusted R Square	Std. error of the estimate	Durbin-Watson
1	.157a	.025	.003	.981	1.854

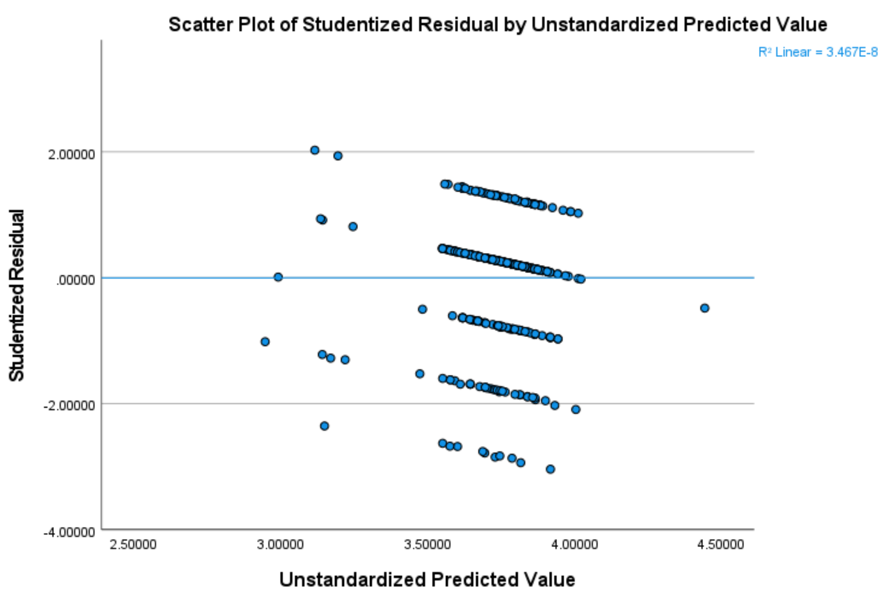
a. Predictors: (Constant), Independent variables: Health insurance status, Monthly number of prescribed medications, Monthly average prescription drug out-of-pocket (OOP) expenses. Co-variables: Race, Age, Education, Income, and Gender.

b. Dependent Variable: Purchase medication over the internet if all medication costs cannot be met

2. Testing for linearity: According to Laerd Statistics (2015), Multiple regression assumes that: (a) the independent variables collectively are linearly related to the dependent variable, and (b) each independent variable is linearly related to the dependent variable. To assess the assumptions (a) and (b): I performed a scatterplot for the studentized residuals (SRE_1) (all independent variables) against the (unstandardized) predicted values (PRE_1) to establish if a linear relationship exists between the dependent and independent variables collectively. As shown in Figure C1 below, the residuals form a horizontal band, indicating the relationship between the dependent and independent variables is likely linear (Laerd Statistics, 2015).

Figure C 1

Scatter Plot of Studentized Residual by Unstandardized Predicted Value: Dependent Variable Likely to Purchase Medication Over the Internet Cost-Savings Strategy



I also conducted “partial regression plots” (partial Plot shown in Figure 5 – 9) to assess the linear relationship between the dependent variable (Likely to Purchase medication over the internet) and each of the continuous independent variables (Age, Income, education, monthly OOP expenses, and the Monthly number of prescribed medication) ignoring any categorical independent variables in the analysis (Health insurance status, Gender, and Race) (Laerd Statistics, 2015).

Figure C 2

Partial Regression Plot: Dependent Variable, Likely to Purchase Medication Over the Internet Cost-Savings Strategy Versus Continuous Independent Variable, Monthly Number of Prescribed Medications

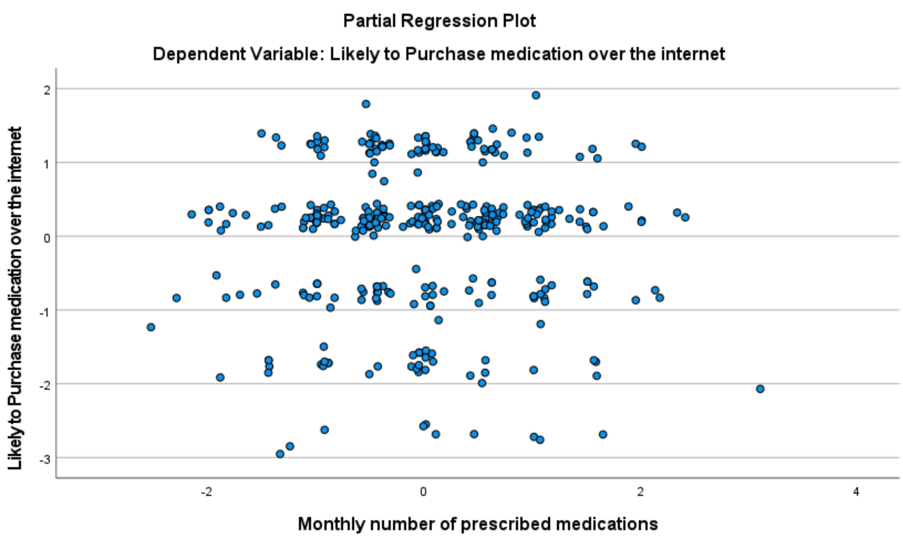


Figure C 3

Partial Regression Plot: Dependent Variable, Likely to Purchase Medication Over the Internet Cost-Savings Strategy Versus Continuous Independent Variable, Monthly Average OOP Expenses

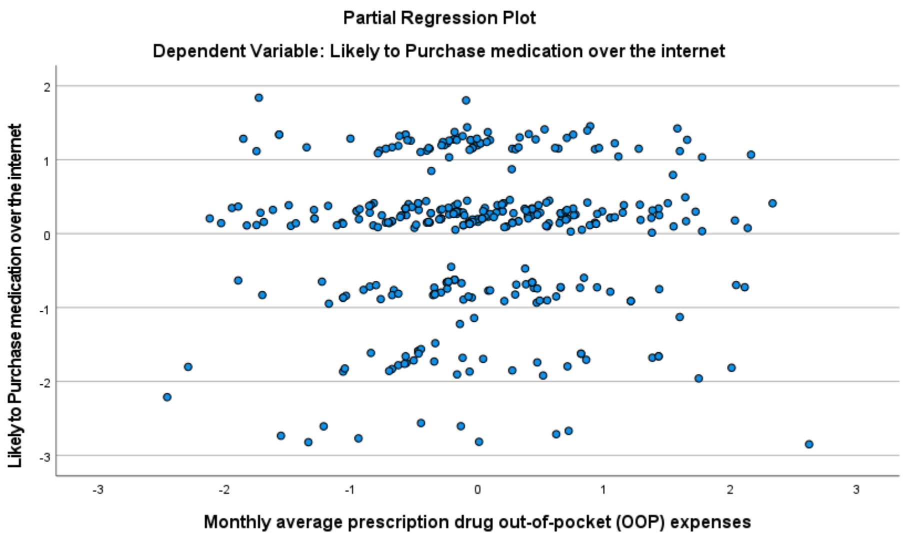


Figure C 4

Partial Regression Plot: Dependent Variable, Likely to Purchase Medication Over the Internet Cost-Savings Strategy Versus Continuous Independent Variable, Income Level

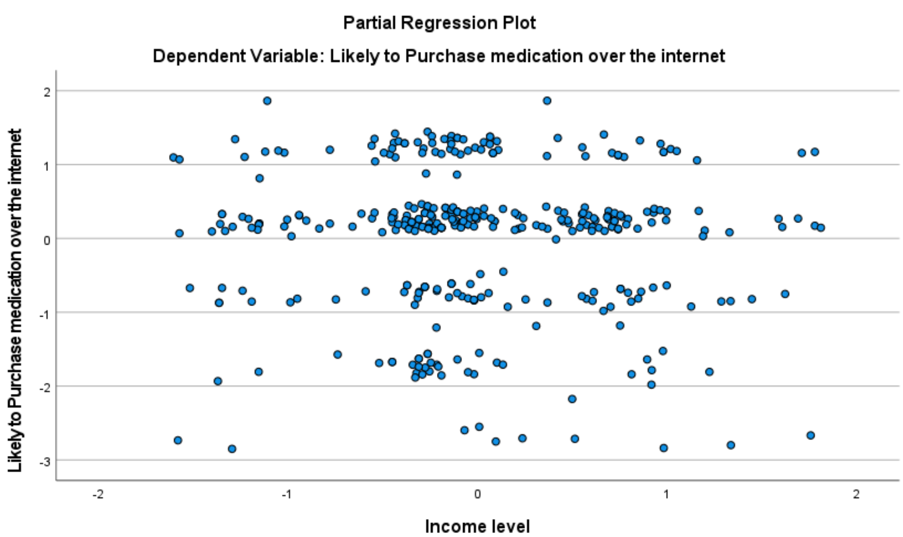


Figure C 5

Partial Regression Plot: Dependent Variable, Likely to Purchase Medication Over the Internet Cost-Savings Strategy Versus Continuous Independent Variable, Educational Level

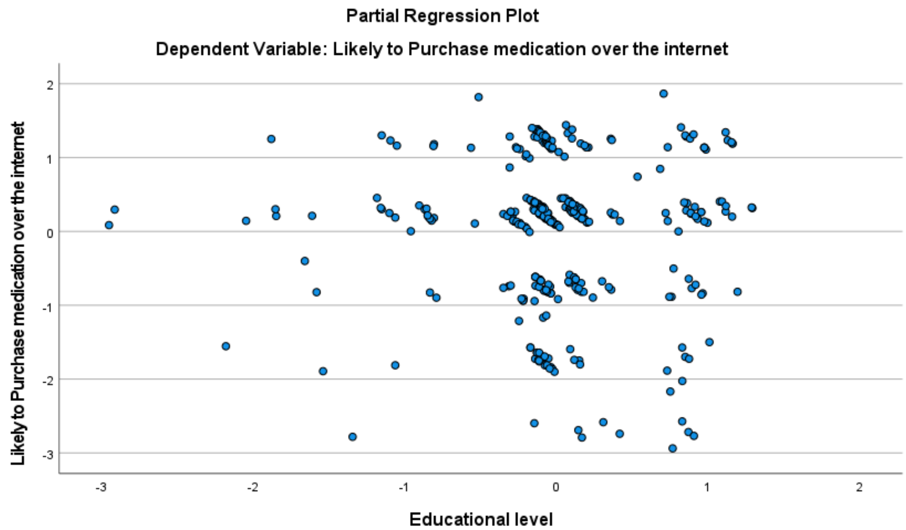
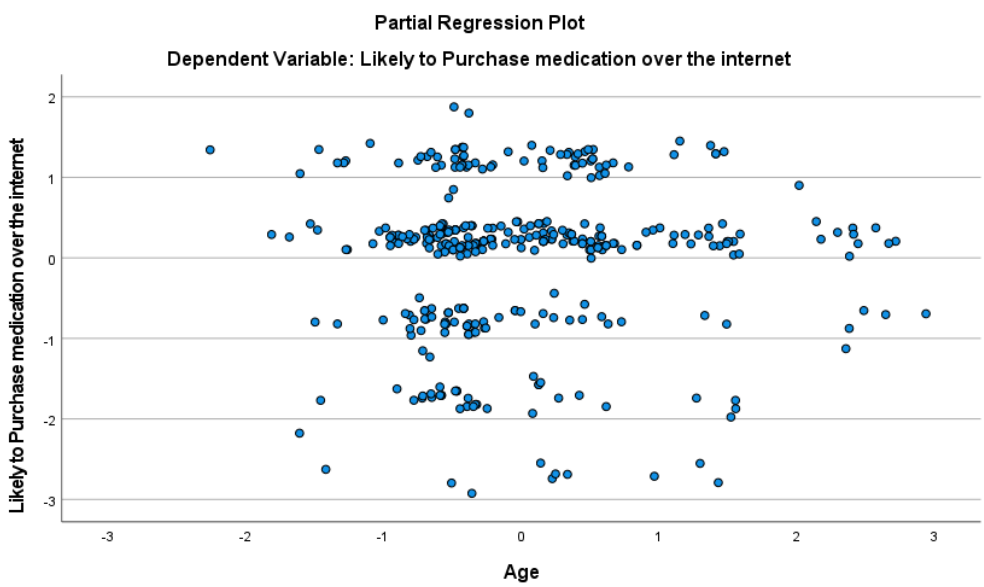


Figure C 6

Partial Regression Plot: Dependent Variable, Likely to Purchase Medication Over the Internet Cost-Savings Strategy Versus Continuous Independent Variable, Average Age of Participants



3. Testing for homoscedasticity: Homoscedasticity assumes that the variance is equal for all predicted dependent variable values (Laerd Statistics, 2015). Assessing Figure 4 by visual inspection, the point of the Plot does not exhibit a pattern but constantly spreads. Therefore, there was homoscedasticity because the spread of the residuals did not appear to increase or decrease across the predicted values (Laerd Statistics, 2015).
4. Checking for multicollinearity: Multicollinearity occurs when two or more independent variables are highly correlated with each other (Laerd Statistics, 2015). I checked this in two stages: I inspected the correlation coefficients and Tolerance/VIF values generated by the SPSS (Laerd Statistics, 2017). None of the independent variables in this data set have Pearson correlations greater than 0.7. and all the Tolerance values are greater than 0.1 (the lowest is 0.766), so confident that there is no problem with collinearity in this particular data set.
5. Checking for unusual points – outliers: No SPSS statistics case diagnostic table has generated an indication that no potential outlier has a studentized residual of more than 3.0. I also assessed the Studentized deleted residuals variables **(** SDR_1), whether these residuals are greater than ±3 standard deviations, no residuals are greater than ±3 standard deviations, therefore no potential outliers (Laerd Statistics, 2015). Leverage points: I examined the variable LEV_1 in the data file, which stores the leverage values for each case. According to Huber (1981), to determine whether any cases exhibit high leverage, leverage values less

than 0.2 as safe, 0.2 to less than 0.5 as risky, and 0.5 and above as dangerous. In this data set, there are no leverage values above the “safe” value of 0.2. Influential points: I checked the Cook’s Distance values that measure the influence for each case. After inspection of the SPSS Statistics variable COO_1 created in the data file, no Cook’s Distance values above 1 in the variables (Leard Statistics, 2015).

6. Checking for normality’s assumption: (a) I assessed the Histogram with a superimposed normal curve and a P-P Plot, both produced in the SPSS statistics Linear Regression Plots dialogue box. The Histogram (shown in figure 10) indicated that the standardized residuals appear to be approximately normally distributed. However, histograms can be deceptive because their appearance can largely depend on selecting the correct bin width (column width) (Laerd Statistics, 2015). I look at the P-P Plot (shown in Figure 11). Although the points are not aligned perfectly along the diagonal line (the distribution is somewhat peaked), they are close enough to indicate that the residuals are close enough to normal for the analysis to proceed (Laerd Statistics, 2015). However, as multiple regression analysis can fairly accept deviation from normality, the result was accepted to mean no transformation needed, and the assumption of normality has not been violated (Laerd Statistics, 2015).

Figure C 7

Histogram of Dependent Variable: Likely to Purchase Medication Over the Internet Cost-Savings Strategy

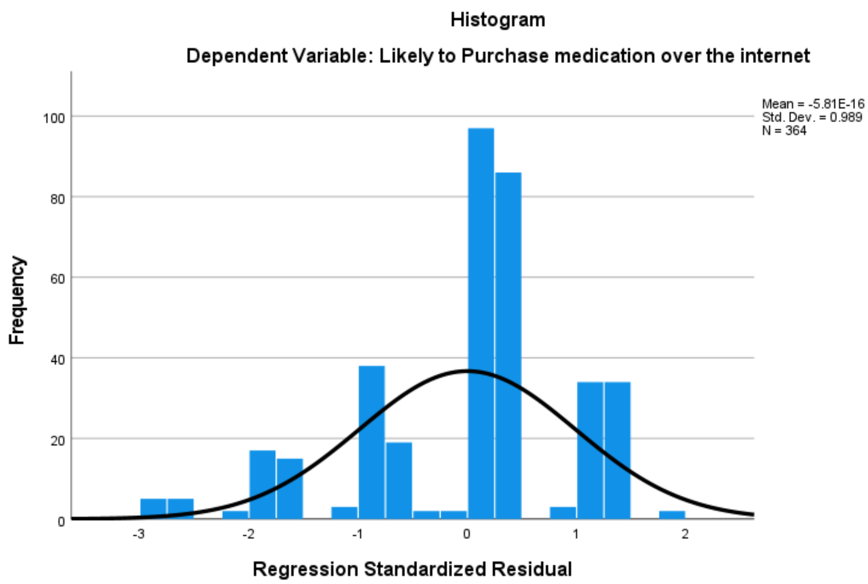
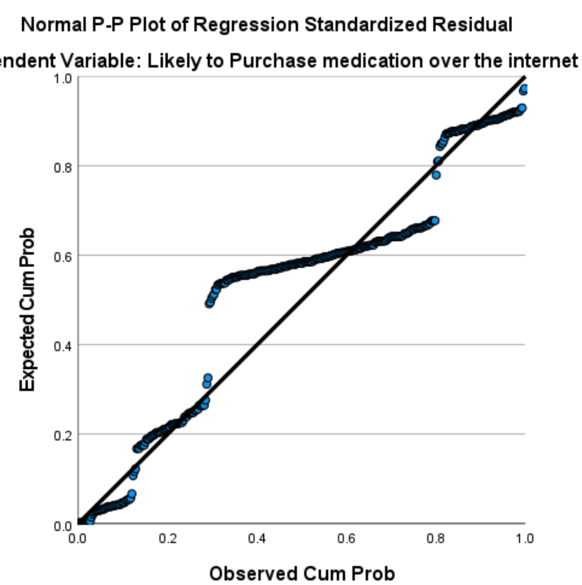


Figure C 8

P-P Plot of Standardized Regression Residual for Dependent Variable: Likely to Purchase Medication Over the Internet Cost-Savings Strategy



Assumption testing RQ4b – Assumptions were run using SPSS version 27 to assess how the data fit the model predicting the likelihood of purchasing medication from other countries in multiple regression analysis:

1. Assumption of Independence of observations – I assessed independently of residuals by Durbin-Watson statistics. The Durbin-Watson (shown in Table 6 below) is 1.773. According to Laerd Statistics (2015), the Durbin-Watson statistic value can range from 0 to 4, but a value of approximately 2 indicates no correlation between residuals. In this analysis, I accepted independent errors (residual).

Table C 2

Descriptive Statistics: Multiple Regression Model Summary Table for the Dependent Variable: Likelihood to Purchase Medication From Other Countries(b)

Model	R	R square	Adjusted R Square	Std. error of the estimate	Durbin-Watson
1	.228[a]	.052	.031	1.050	1.773

a. Predictors: (Constant), Independent variables: Health insurance status, Monthly number of prescribed medications, Monthly average prescription drug out-of-pocket (OOP) expenses. Co-variables: Race, Age, Education, Income, and Gender.
b. Dependent Variable: Purchase medication from other countries if all medication costs cannot be met

2. Testing for linearity: According to Laerd Statistics (2015), Multiple regression assumes that: (a) the independent variables collectively are linearly related to the dependent variable, and (b) each independent variable is linearly related to the dependent variable. To assess the assumptions (a) and (b): I performed a scatterplot for the studentized residuals (SRE_2) (all independent variables)

against the (unstandardized) predicted values (PRE_2) to establish if a linear relationship exists between the dependent and independent variables collectively. As shown in Figure 12 below, the residuals form a horizontal band, indicating the relationship between the dependent and independent variables is likely linear (Laerd Statistics, 2015). (b). I also conducted “partial regression plots” (partial Plot shown in Figure 13 – 17) to assess the linear relationship between the dependent variable (Likely to Purchase medication from other countries) and each of the continuous independent variables (Age, Income, education, monthly OOP expenses, and the Monthly number of prescribed medication) ignoring any categorical independent variables in the analysis (Health insurance status, Gender, and Race) (Laerd Statistics, 2015).

Figure C 9

Scatter Plot of Studentized Residual by Unstandardized Predicted Value: Dependent Variable Likely to Purchase Medication From Other Countries Cost-Savings Strategy

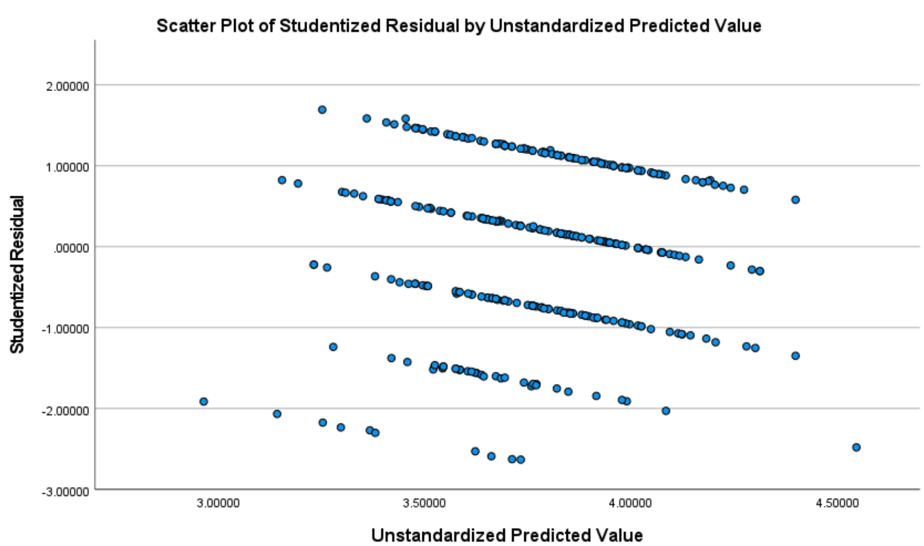


Figure C 10

Partial Regression Plot: Dependent Variable, Likely to Purchase Medication From Other Countries Cost-Savings Strategy Versus Continuous Independent Variable, Age of Participants

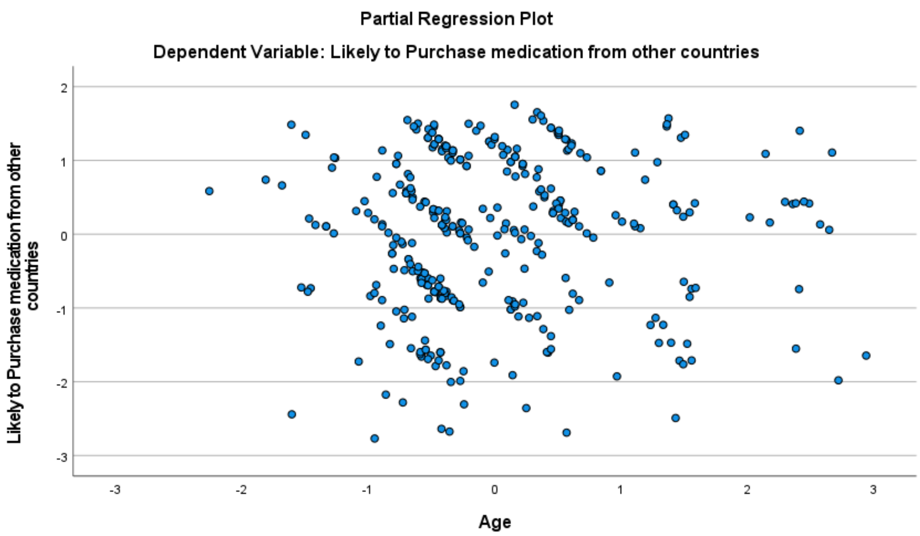


Figure C 11

Partial Regression Plot: Dependent Variable, Likely to Purchase Medication From Other Countries Cost-Savings Strategy Versus Continuous Independent Variable, Educational Level

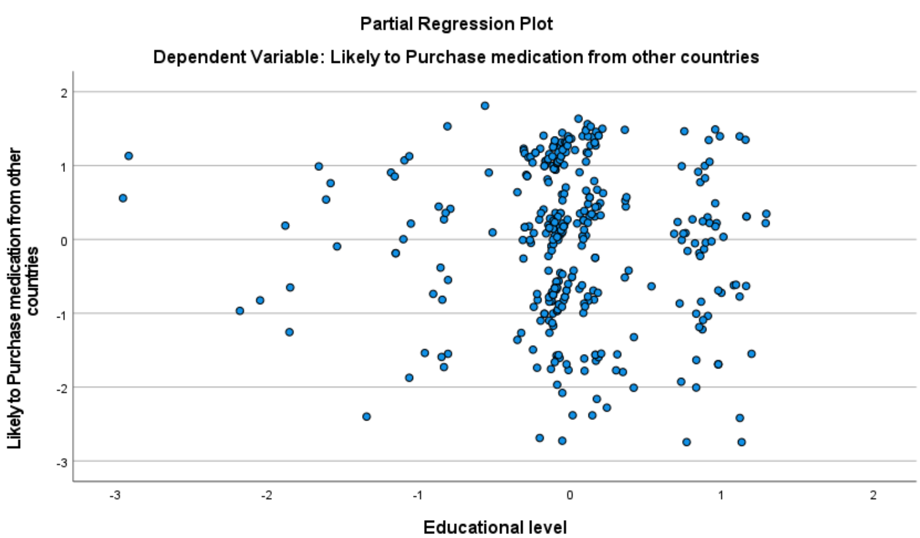


Figure C 12

Partial Regression Plot: Dependent Variable, Likely to Purchase Medication From Other Countries Cost-Savings Strategy Versus Continuous Independent Variable, Income Level

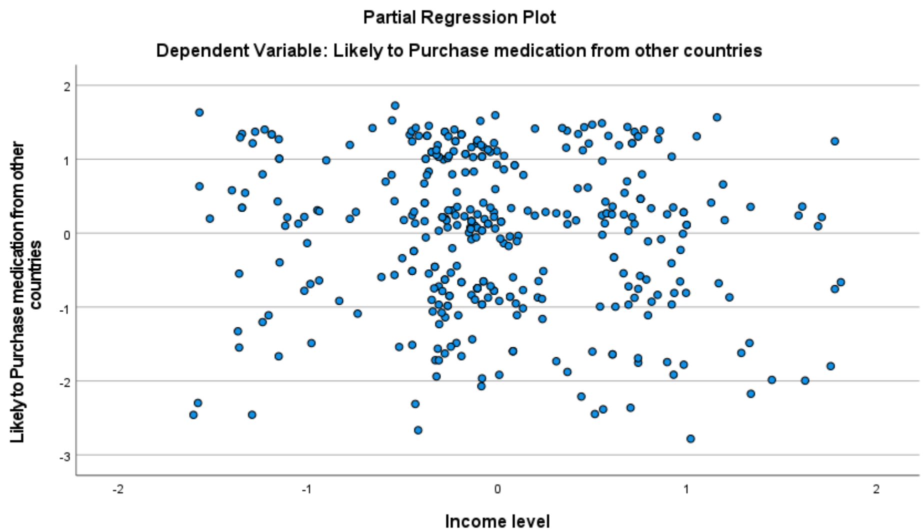


Figure C 13

Partial Regression Plot: Dependent Variable, Likely to Purchase Medication From Other Countries Cost-Savings Strategy Versus Continuous Independent Variable, Monthly Number of Prescribed Medication

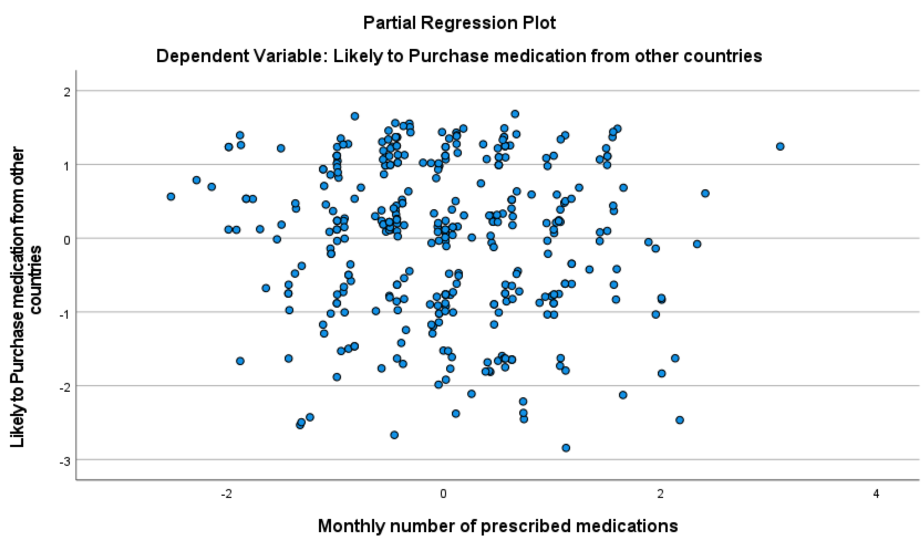
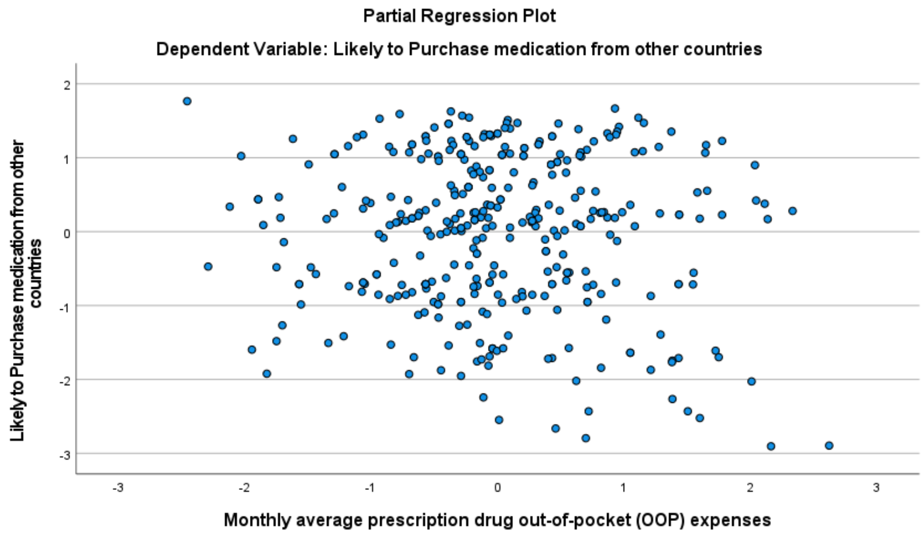


Figure C 14

Partial Regression Plot: Dependent Variable, Likely to Purchase Medication From Other Countries Cost-Savings Strategy Versus Continuous Independent Variable, Monthly Average OOP Expenses



3. Testing for homoscedasticity: Homoscedasticity assumes that the variance is equal for all predicted dependent variable values (Laerd Statistics, 2015). Assessing Figure 12 by visual inspection, the point of the Plot does not exhibit a pattern but constantly spreads. Therefore, there was homoscedasticity because the spread of the residuals did not appear to increase or decrease across the predicted values (Laerd Statistics, 2015).
4. Checking for multicollinearity: Multicollinearity occurs when two or more independent variables are highly correlated with each other (Laerd Statistics, 2015). I assessed this in two stages: I inspected the correlation coefficients and Tolerance/VIF values generated by the SPSS (Laerd Statistics, 2015). None of the independent variables in this data set have Pearson

correlations greater than 0.7. and all the Tolerance values are greater than 0.1 (the lowest is 0.766), so confident that there is no problem with collinearity in this particular data set.

5. Checking for unusual points – outliers: No SPSS statistics case diagnostic table was generated, indicating that no potential outlier has a studentized residual of more than 3.0. I also assessed the Studentized deleted residuals variables **(** SDR_2), whether these residuals are greater than ±3 standard deviations, no residuals are greater than ±3 standard deviations, therefore no potential outliers (Laerd Statistics, 2015). Leverage points: I examined the variable LEV_2 in the data file, which stores the leverage values for each case. According to Huber (1981), to determine whether any cases exhibit high leverage, leverage values less than 0.2 as safe, 0.2 to less than 0.5 as risky, and 0.5 and above as dangerous. In this data set, there are no leverage values above the "safe" value of 0.2. Influential points: I checked the Cook's Distance values that measure the influence for each case. After inspection of SPSS Statistics variable COO_2 created in the data file, there are no Cook's Distance values above 1 in the variables (Laerd Statistics, 2015).
6. Checking for normality's assumption: (a) I assessed the Histogram with a superimposed normal curve and a P-P Plot, both produced in the SPSS statistics Linear Regression Plots dialogue box. The Histogram (shown in figure 18) indicated that the standardized residuals appear to be approximately normally distributed. However, histograms can be deceptive because their appearance can

largely depend on selecting the correct bin width (column width) (Laerd Statistics, 2015). I look at the P-P Plot (shown in Figure 19). Although the points are not aligned perfectly along the diagonal line (the distribution is somewhat peaked), they are close enough to indicate that the residuals are close enough to normal for the analysis to proceed (Laerd Statistics, 2015). However, as multiple regression analysis can fairly accept deviation from normality, the result was accepted to mean no transformation is needed, and the assumption of normality has not been violated (Laerd Statistics, 2015).

Figure C 15

Histogram of Dependent Variable: Likely to Purchase Medication From Other Countries Cost-Savings Strategy

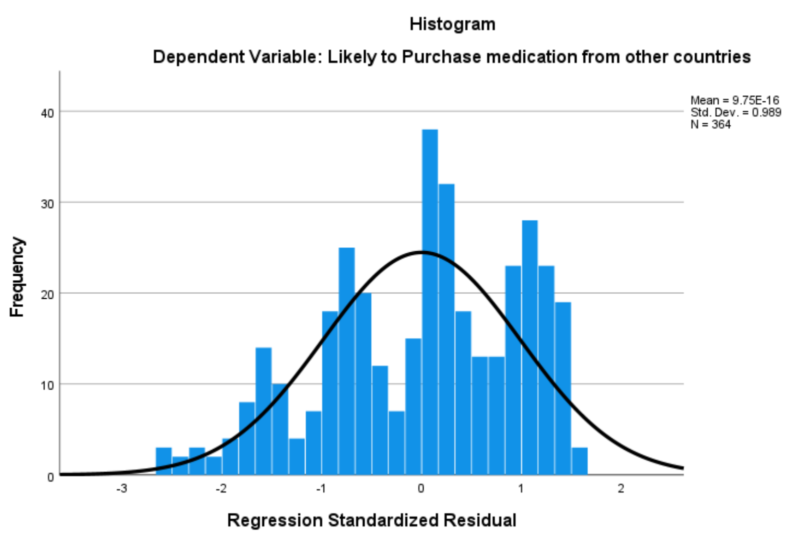
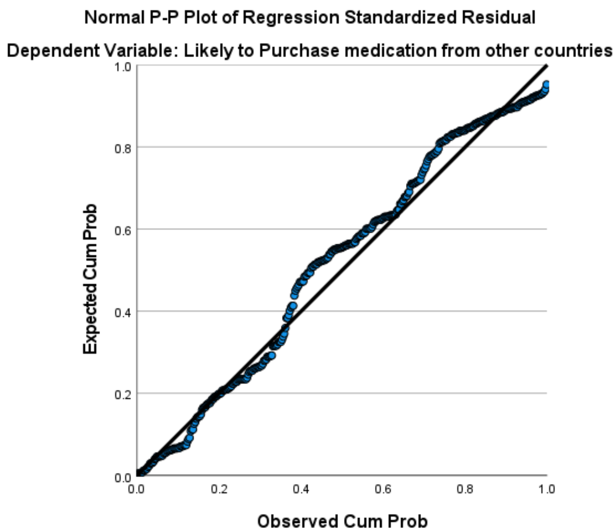


Figure C 16

P-P plot of Standardized Regression Residual for Dependent Variable: Likely to Purchase Medication From Other Countries Cost-Savings Strategy



Testing assumptions RQ4c – Assumptions were run using SPSS version 27 to assess how the data fit the model predicting the likelihood of obtaining free samples from doctors or patient assistance programs in multiple regression analysis:

1. Assumption of Independence of observations – I assessed independently of residuals by Durbin-Watson statistics. The Durbin-Watson (shown in Table 7 below) is 2.103. According to Laerd Statistics (2015), the Durbin-Watson statistic value can range from 0 to 4, but a value of approximately 2 indicates no correlation between residuals. However, in this analysis, the observation may not have been entered into SPSS Statistics on the expected order for autocorrelation. The test result may not be correct, so there is no reason for the observation to be related (Laerd Statistics, 2015). I accepted that there are independent errors (residual).

Table C 3

Descriptive Statistics: Multiple Regression Model Summary Table for the Dependent Variable: Likelihood to Obtain Free Samples From Doctors or Patient Assistance Program(b)

Model	R	R square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.160[a]	.025	.004	.817	2.103

a. Predictors: (Constant), Independent variables: Health insurance status, Monthly number of prescribed medications, Monthly average prescription drug out-of-pocket (OOP) expenses. Co-variables: Race, Age, Education, Income, and Gender.
b. Dependent Variable: Obtain free samples from doctors or patient assistance programs if all medication costs cannot be met

2. Testing for linearity: According to Laerd Statistics (2015), Multiple regression assumes that: (a) the independent variables collectively are linearly related to the dependent variable, and (b) each independent variable is linearly related to the dependent variable. To assess the assumptions (a) and (b): I performed a scatterplot for the studentized residuals (SRE_3) (all independent variables) against the (unstandardized) predicted values (PRE_3) to establish if a linear relationship exists between the dependent and independent variables collectively. As shown in Figure 20 below, the residuals form a horizontal band, indicating the relationship between the dependent and independent variables is likely linear (Laerd Statistics, 2015). (b). I also conducted a “partial regression plots” analysis (partial Plot shown in Figure 21 – 25) to assess the linear relationship between the dependent variable (Likely to Purchase medication from other countries) and each of the continuous independent variables (age, income, education, monthly OOP expenses, and monthly

number of prescribed medication) ignoring any categorical independent variables in the analysis (Health insurance status, Gender, and Race; Laerd Statistics, 2015).

Figure C 17

Scatter Plot of Studentized Residual by Unstandardized Predicted Value: Dependent Variable Likely to Obtain Free Samples From Doctors or Patient Assistant Program Cost-Savings Strategy

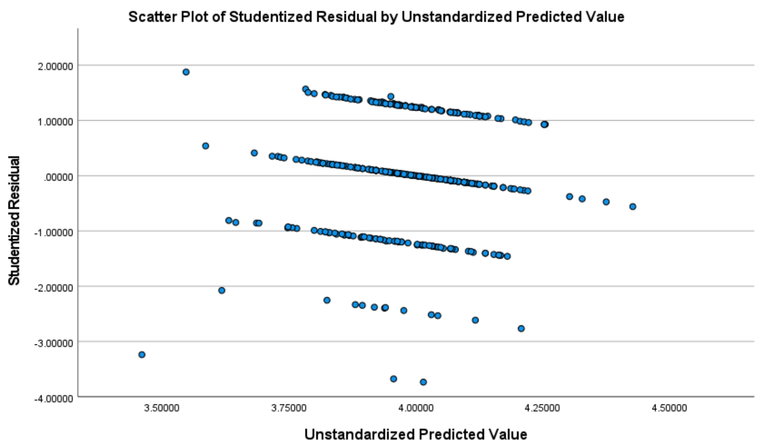


Figure C 18

Partial Regression Plot: Dependent Variable, Likely to Obtain Free Samples From Doctors or Patient Assistance Program Cost-Savings Strategy Versus Continuous Independent Variable, Age of Participants

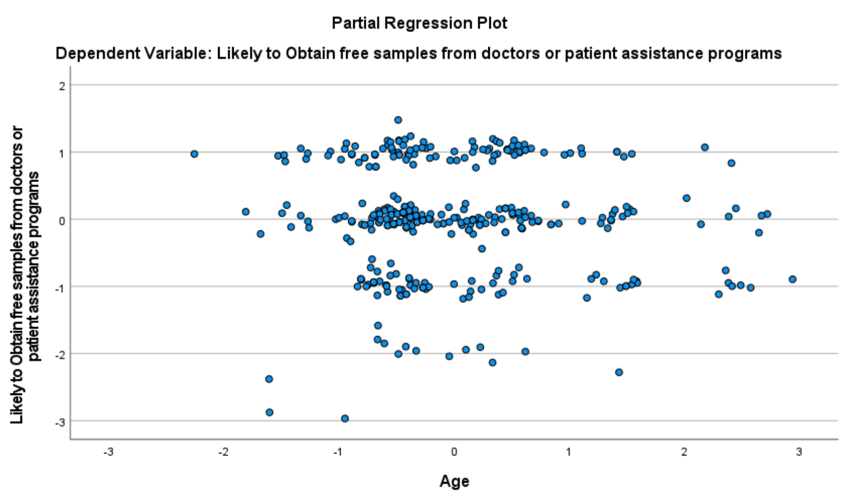


Figure C 19

Partial Regression Plot: Dependent Variable, Likely to Obtain Free Samples From Doctors or Patient Assistance Program Cost-Savings Strategy Versus Continuous Independent Variable, Educational Level

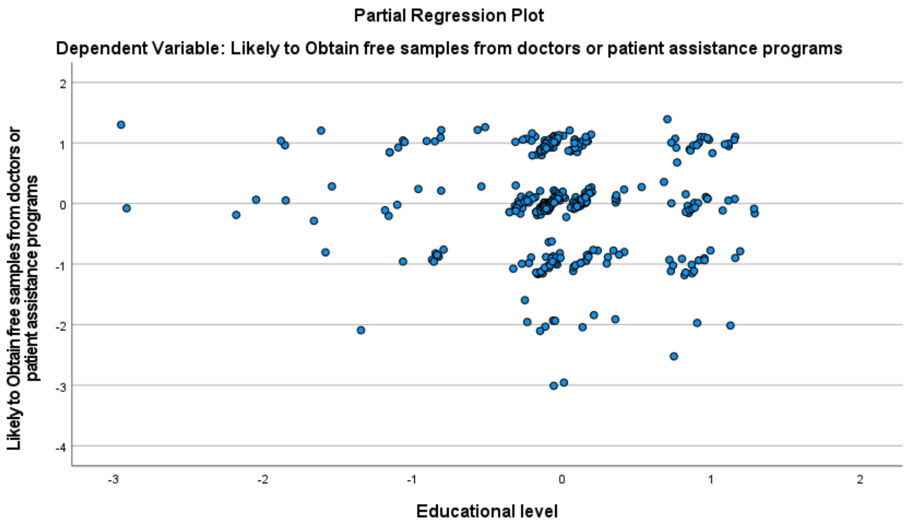


Figure C 20

Partial Regression Plot: Dependent Variable, Likely to Obtain Free Samples From Doctors or Patient Assistance Program Cost-Savings Strategy Versus Continuous Independent Variable, Income Level

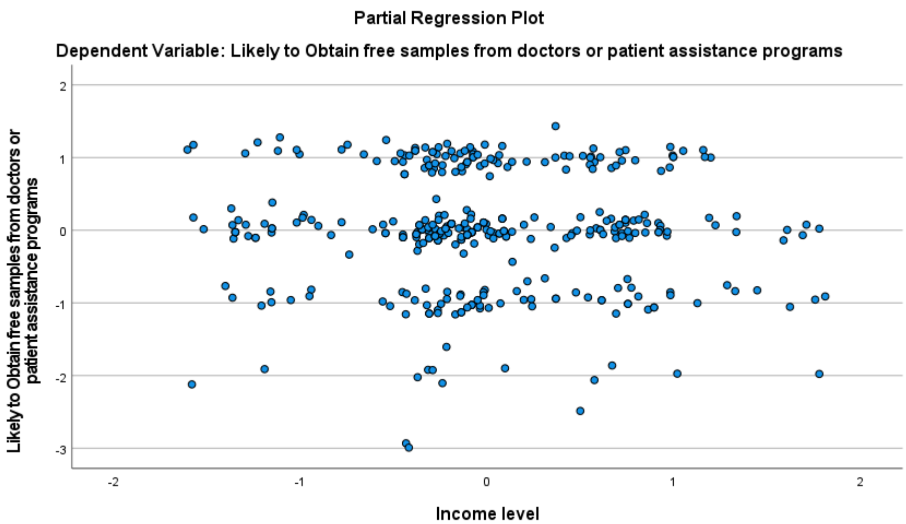


Figure C 21

Partial Regression Plot: Dependent Variable, Likely to Obtain Free Samples From Doctors or Patient Assistance Program Cost-Savings Strategy Versus Continuous Independent Variable, Monthly Number of Prescribed Medication

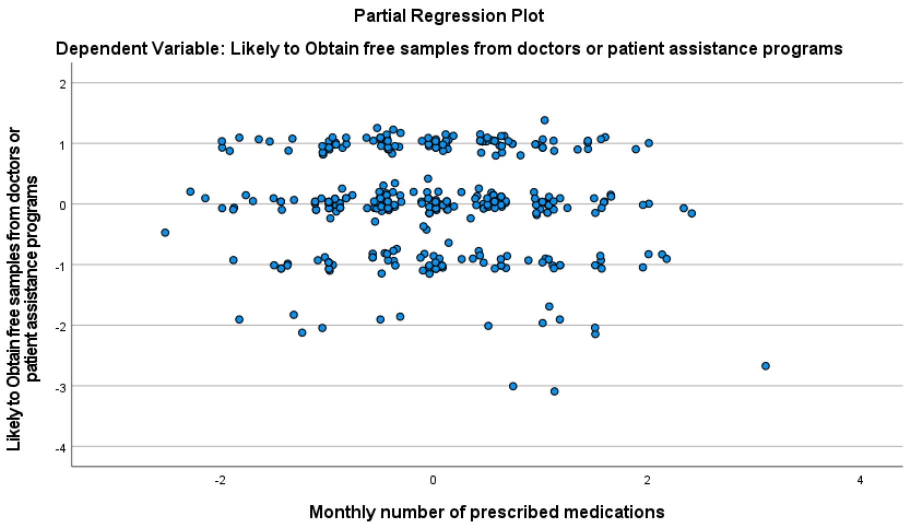
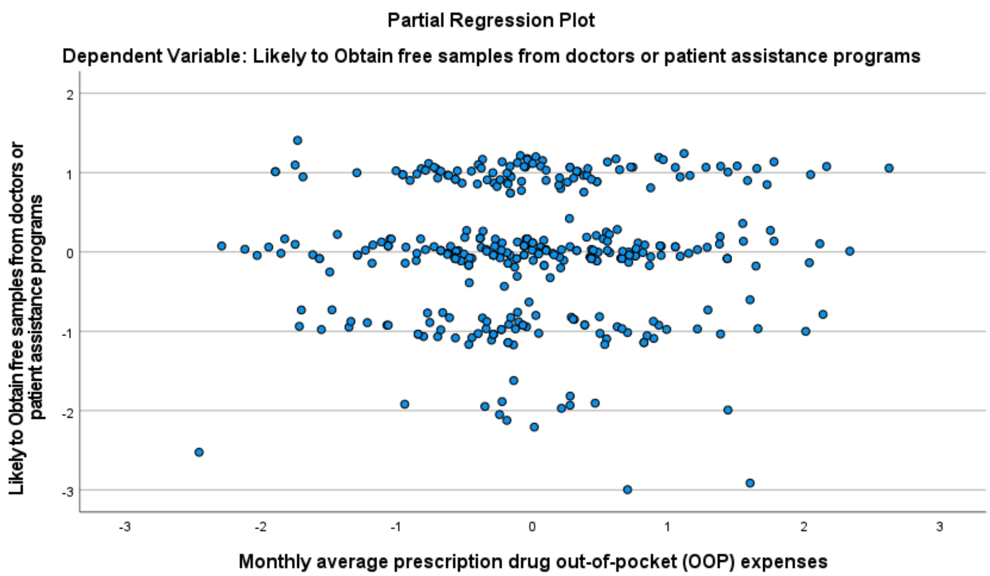


Figure C 22

Partial Regression Plot: Dependent Variable, Likely to Obtain Free Samples From Doctors or Patient Assistance Program Cost-Savings Strategy Versus Continuous Independent Variable, Monthly Average OOP Expenses



3. Testing for homoscedasticity: Homoscedasticity assumes that the variance is equal for all predicted dependent variable values (Laerd Statistics, 2015). Assessing Figure 20 by visual inspection, the point of the Plot does not exhibit a pattern but constantly spreads. Therefore, there was homoscedasticity because the spread of the residuals did not appear to increase or decrease across the predicted values (Laerd Statistics, 2015).
4. Checking for multicollinearity: Multicollinearity occurs when two or more independent variables are highly correlated with each other (Laerd Statistics, 2015). I assessed this in two stages: I inspected the correlation coefficients and Tolerance/VIF values generated by the SPSS (Laerd Statistics, 2015). None of the independent variables in this data set have Pearson correlations greater than 0.7. and all the Tolerance values are greater than 0.1 (the lowest is 0.766), so confident that there is no problem with collinearity in this particular data set.
5. Checking for unusual points – outliers: I inspected the case diagnostic table generated by the SPSS statistics. It indicated that three potential outliers might have a studentized residual of more than 3.0. I checked whether the Studentized deleted residuals variables (SDR_3) generated in the SPSS statistics data view were greater than ±3 standard deviations. Still, none were found. Therefore, those potential outliers were kept in the analysis. (Laerd Statistics, 2015). Leverage points: I examined the variable LEV_3 in the data file, which stores the leverage values for each case. According to Huber (1981), to determine whether any cases

exhibit high leverage, leverage values less than 0.2 as safe, 0.2 to less than 0.5 as risky, and 0.5 and above as dangerous. In this data set, there are no leverage values above the "safe" value of 0.2. Influential points: I checked the Cook's Distance values that measure the influence for each case. After inspection of SPSS Statistics variable COO_3 created in the data file, there are no Cook's Distance values above 1 in the variables (Laerd Statistics, 2015).

6. Checking for normality's assumption: (a) I assessed the Histogram with a superimposed normal curve and a P-P Plot, both produced in the SPSS statistics Linear Regression Plots dialogue box. The Histogram (shown in figure 26) indicated that the standardized residuals appear to be approximately normally distributed. However, histograms can be deceptive because their appearance can largely depend on selecting the correct bin width (column width) (Laerd Statistics, 2015). I look at the P-P Plot (shown in Figure 27). Although the points are not aligned perfectly along the diagonal line (the distribution is somewhat peaked), they are close enough to indicate that the residuals are normal for the analysis to proceed (Laerd Statistics, 2015). As multiple regression analysis can fairly accept deviation from normality, the result was accepted to mean no transformation needed, and the assumption of normality has not been violated.

Figure C 23

Histogram of Dependent Variable: Likely to Obtain Free Samples From Doctors or Patient Assistance Programs Cost-Savings Strategy

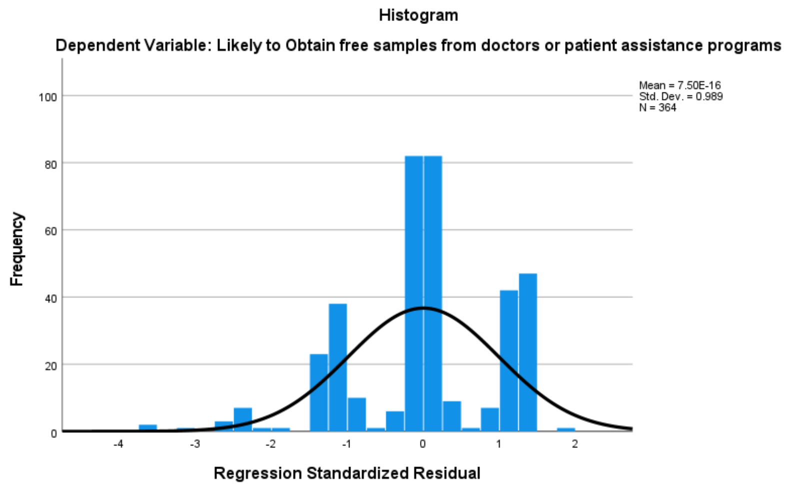
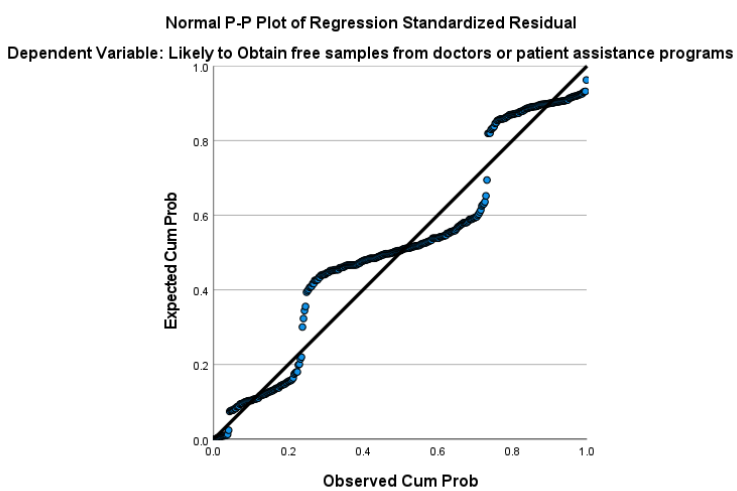


Figure C 24

P-P plot of Standardized Regression Residual for Dependent Variable: Likely to Obtain Free Samples From Doctors or Patient Assistance Programs Cost-Savings Strategy



Assumption testing RQ4d - Assumptions were run using SPSS version 27 to assess how the data fit the model predicting the likelihood of Split pills or changing the dosage frequency in multiple regression analysis:

1. Assumption of Independence of observations – I assessed independently of residuals by Durbin-Watson statistics. The Durbin-Watson (shown in Table 23 below) is 1.952. According to Laerd Statistics (2015), the Durbin-Watson statistic value can range from 0 to 4, but a value of approximately 2 indicates no correlation between residuals. I accepted that there is independent of errors (residual).

Table C 4

Descriptive Statistics: Multiple Regression Model Summary Table for the Dependent Variable: Likelihood to Split Pills or Change the Dosage Frequency(b)

Model	R	R square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.331[a]	.109	.089	.929	1.952

a. Predictors: (Constant), Independent variables: Health insurance status, Monthly number of prescribed medications, Monthly average prescription drug out-of-pocket (OOP) expenses. Co-variables: Race, Age, Education, Income, and Gender.
b. Dependent Variable: Split pills or change the dosage frequency if all medication costs cannot be met

2. Testing for linearity: According to Laerd Statistics (2015), Multiple regression assumes that: (a) the independent variables collectively are linearly related to the dependent variable, and (b) each independent variable is linearly related to the dependent variable. To assess the assumptions (a) and (b): I performed a scatterplot for the studentized residuals (SRE_4) (all independent variables)

against the (unstandardized) predicted values (PRE_4) to establish if a linear relationship exists between the dependent and independent variables collectively. As shown in Figure 28 below, the residuals form a horizontal band, indicating the relationship between the dependent and independent variables is likely linear (Laerd Statistics, 2015). (b). I also conducted a "partial regression plots" analysis (partial Plot shown in Figure 29 – 33) to assess the linear relationship between the dependent variable (Likely to Split pills or change dosage frequency) and each of the continuous independent variables (age, income, education, monthly OOP expenses, and the Monthly number of prescribed medication) ignoring any categorical independent variables in the analysis (Health insurance status, Gender, and Race) (Laerd Statistics, 2015).

Figure C 25

Scatter Plot of Studentized Residual by Unstandardized Predicted Value: Dependent Variable Likely Split Pills or Change Dosage Frequency Cost-Savings Strategy

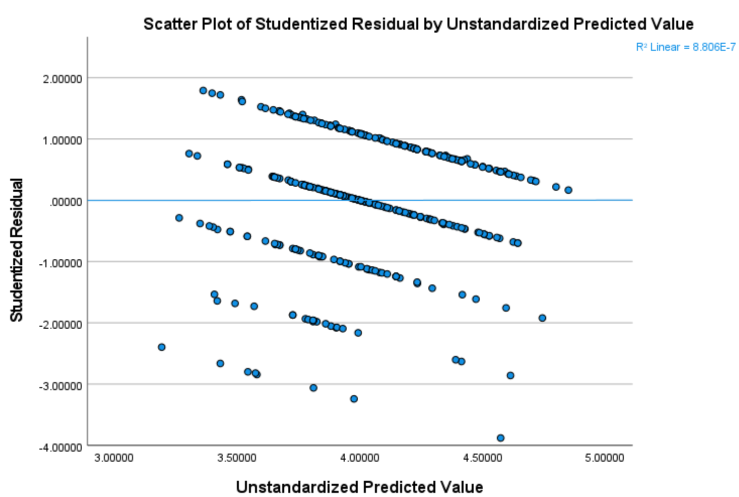


Figure C 26

Partial Regression Plot: Dependent Variable, Split Pills or Change Dosage Frequency Cost-Savings Strategy Versus Continuous Independent Variable - Age of Participants

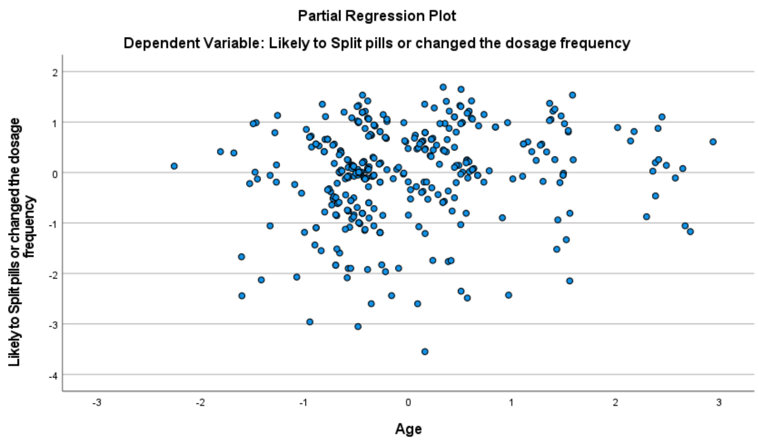


Figure C 27

Partial Regression Plot: Dependent Variable, Split Pills or Change Dosage Frequency Cost-Savings Strategy Versus Continuous Independent Variable - Educational Level

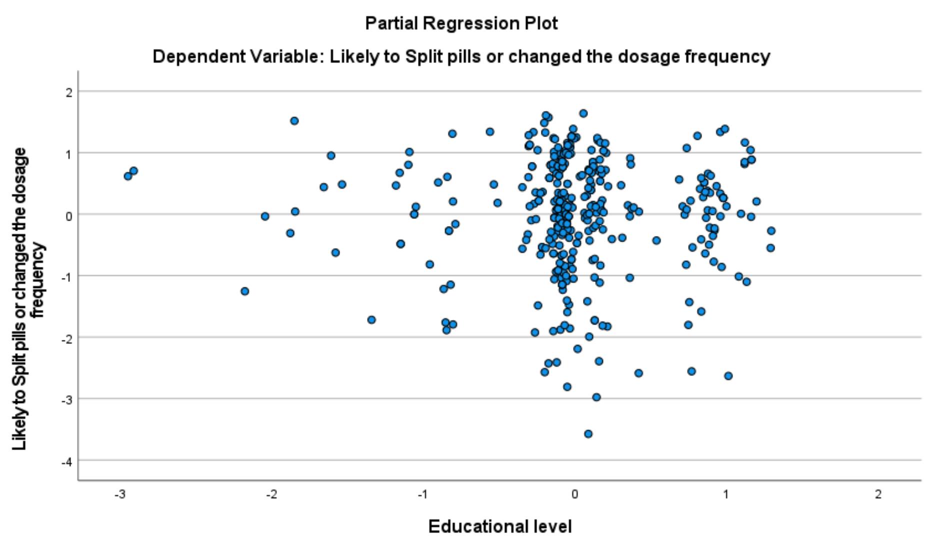


Figure C 28

Partial Regression Plot: Dependent Variable, Split Pills or Change Dosage Frequency Cost-Savings Strategy Versus Continuous Independent Variable, Income Level

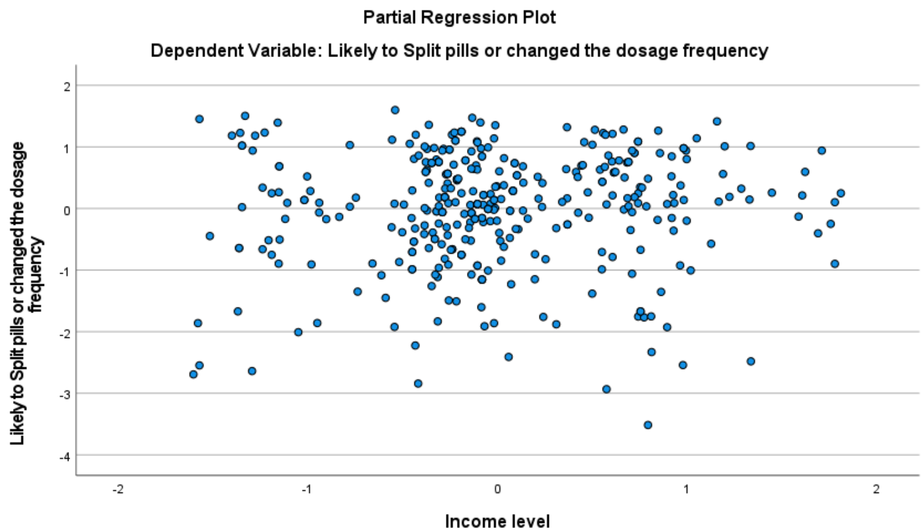


Figure C 29

Partial Regression Plot: Dependent Variable, Split Pills or Change Dosage Frequency Cost-Savings Strategy Versus Independent Variable, Monthly Number of Prescribed Medication

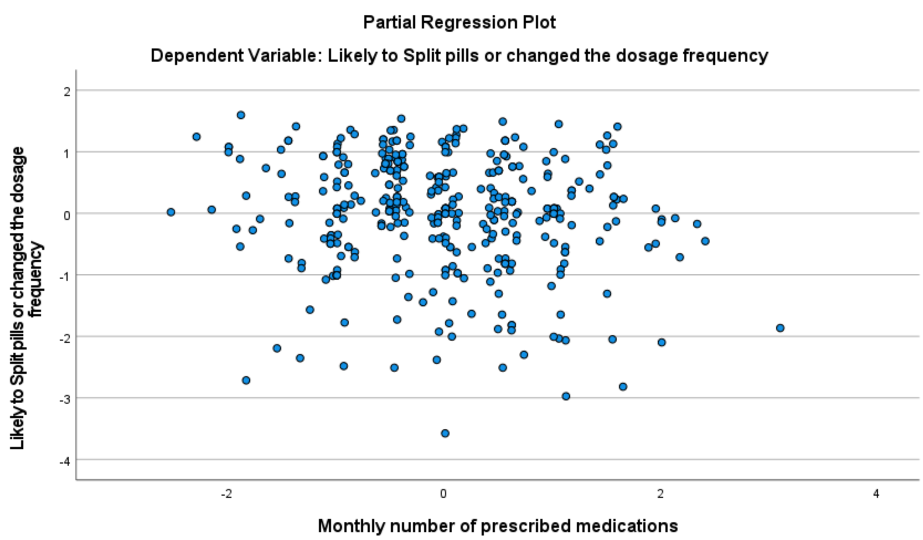
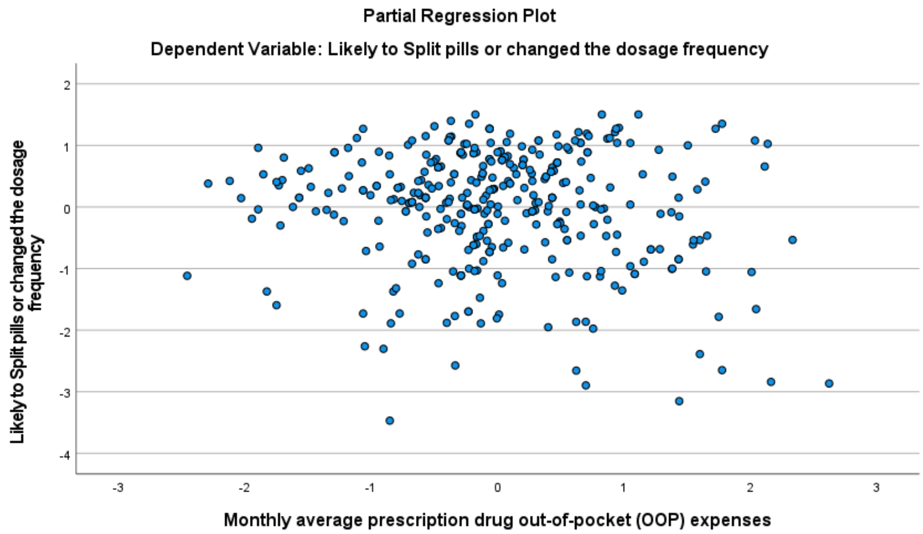


Figure C 30

Partial Regression Plot: Dependent Variable, Split Pills or Change Dosage Frequency Cost-Savings Strategy Versus Independent Variable- Monthly Average OOP Expenses



3. Testing for homoscedasticity: Homoscedasticity assumes that the variance is equal for all predicted dependent variable values (Laerd Statistics, 2015). Assessing Figure 28 by visual inspection, the point of the Plot does not exhibit a pattern but constantly spreads. Therefore, there was homoscedasticity because the spread of the residuals did not appear to increase or decrease across the predicted values (Laerd Statistics, 2015).
4. Checking for multicollinearity: Multicollinearity occurs when two or more independent variables are highly correlated with each other (Laerd Statistics, 2015). I assessed this in two stages: I inspected the correlation coefficients and Tolerance/VIF values generated by the SPSS (Laerd Statistics, 2015). None of the independent variables in this data set have Pearson correlations greater than 0.7. and all the Tolerance values are greater than 0.1 (the

lowest is 0.766), so confident that there is no problem with collinearity in this particular data set.

5. Checking for unusual points – outliers: I inspected the case diagnostic table generated by the SPSS statistics. It indicated that three potential outliers might have a studentized residual of more than 3.0. I checked whether the Studentized deleted residuals variables (SDR_4) generated in the SPSS statistics data view were greater than ±3 standard deviations. Still, none were found. Therefore, those potential outliers were kept in the analysis. (Laerd Statistics, 2015). Leverage points: I examined the variable LEV_4 in the data file, which stores the leverage values for each case. According to Huber (1981), to determine whether any cases exhibit high leverage, leverage values less than 0.2 as safe, 0.2 to less than 0.5 as risky, and 0.5 and above as dangerous. In this data set, there are no leverage values above the "safe" value of 0.2. Influential points: I checked the Cook's Distance values that measure the influence for each case. After inspection of the SPSS Statistics variable COO_4 created in the data file, no Cook's Distance values above 1 in the variables (Laerd Statistics, 2015).
6. Checking for normality's assumption: (a) I assessed the Histogram with a superimposed normal curve and a P-P Plot, both produced in the SPSS statistics Linear Regression Plots dialogue box. The Histogram (shown in figure 34) indicated that the standardized residuals appear to be approximately normally distributed. However, histograms can be deceptive because their appearance can largely depend on selecting the correct bin width (column width) (Laerd Statistics,

2015). I look at the P-P Plot (shown in Figure 35). Although the points are not aligned perfectly along the diagonal line (the distribution is somewhat peaked), they are close enough to indicate that the residuals are close enough to normal for the analysis to proceed (Laerd Statistics, 2015).

Figure C 31

Histogram of Dependent Variable: Likely to Split Pills or Change the Dosage Frequency Cost-Savings Strategy

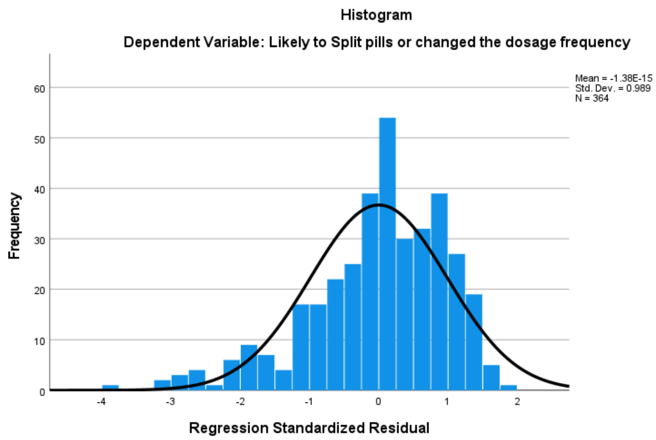


Figure C 32

P-P plot of Standardized Regression Residual for Dependent Variable: Likely to Split Pills or Changed Dosage Frequency Cost-Savings Strategy