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Social Distance Compliance and Perceived Importance of Online YouTube Diabetes Prevention Programs

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This is to certify that the doctoral dissertation by

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has been found to be complete and satisfactory in all respects,
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Walden University
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Abstract

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MA, Walden University, 2020

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Dissertation Submitted in Partial Fulfillment

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Abstract

This quantitative, nonexperimental survey was designed using a five-point Likert scale to measure the differences in the perceived importance scores for enrollment practices into nationally accredited YouTube diabetes prevention programs, or YouTube DPP, among online U.S. adult participants during the COVID-19 pandemic based on the social cognitive framework and was validated with Cronbach's alpha. G* Power analysis for alpha level = 0.05, standard power = 0.08, and the effect size = 0.25 was calculated for a target population of over 100,000. Responses (i.e., $N = 258$) from the COVID-19 Blood Sugar Wellness Survey were uploaded from SurveyMonkey. The perceived important scores of the participants were categorized into five social distance compliance groups. Descriptive statistics and a one-way analysis of variance (ANOVA) were used and the perceived important scores between the social distance compliance groups were observed to be significantly different, $F(4, 253) = 7.36$, $p < .001$, $\eta^2 = 0.104$. Based on Tukey's post hoc test, there were higher perceived importance scores for compliant, highly compliant, and always compliant groups when compared to low compliance group scores. Also, COVID-19 mandates impacted the participant's interest to enroll into YouTube DPP when presented with face-to-face (36.8%) or online doctor referrals (22.5%), program insurance coverage (30.6%), and programs with smartphone compatibility (27.9%). Percentages below 20% were classified as of low interest. Thus, policy makers should devise program incentives for clinician referrals, insurance coverage, and smartphone applications to increase enrollment rates into nationally accredited YouTube DPP.

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Dedication

This work is dedicated to my grandfather, grandmothers, aunts, uncles, and cousins that started the journey with us, but were unable to be here on completion. We know that they are here with us in spirt. I also dedicate this work to my mother, father, sisters, brothers, and dozens of cousins, aunts and uncles, extended family members, friends, neighbors, and coworkers. Finally, I dedicate this work to God. Thank you, Lord, for all your blessings in completing this work.

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If it were not for my family, friends, and faculty at Walden University, this part of my life's journey would not have taken place. Thank you for all your support and patience. I am the luckiest to have been surrounded by such loving and devoted family and friends. Dr. Jill Nolan and Dr. Beverly Neville were both my guiding light of inspiration through it all. I pray that you both continue to work tremendously towards a future filled with the blessings that you have bestowed on me and countless others. That the return in your lives for your contribution be filled with every ounce of fulfillment that you both have given. Thank you all. My desire is to continue the work to bring about positive social change in our communities through the valued lessons that you all have taught me. And as long as you are with me in mind and spirit, I know together we can change were we, work, learn, live, play, and pray for good.

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Chapter 1: Introduction to the Study

In the United States, one in five adults are diagnosed and live with type 2 diabetes each day, and one in three adults are prediabetic (CDC, 2020). The cost to treat the disease is staggering, totaling more than $320 billion annually (ADA, 2020). National Diabetes Prevention Programs (DPP) have been established to contain the diabetic epidemic through health education and advocacy (Madrigal & Mannan, 2020; CDC, 2020). Individuals must be screened and tested for prediabetes or type 2 diabetes for enrollment into DPP (CDC, 2020). Yet, enrollment into these programs is low despite intense marketing campaigns and recruitment strategies (Holliday, 2019). COVID-19 social distancing mandates further complicates recruitment practices (Plohl & Musil, 2021). Thus, research was conducted to clarify this dilemma and provide evidence supporting the need for better YouTube diabetes prevention programs (YouTube DPP) during the COVID-19 pandemic. I did so by analyzing social distance compliance (SDC) levels identified from government mandates and personal beliefs or norms concerning the mandates, and the perceived importance (PI) of enrollment practices and expectations of getting formal type 2 diabetes education and type 2 diabetes self-management from YouTube DPP videos.

In addition, it is assumed that social distancing mandates and the disruptive climate created by the pandemic promote an increased reliance on mobile communication and online activity (Yin et al., 2020). This assumption further supported the need to conduct relevant research identifying the importance of YouTube DPP to the public during pandemics like COVID-19 to help manage type 2 diabetes. This chapter focused on a brief explanation of the gaps identified within the discipline through evidence-based research with relevance to SDC and the importance of recruitment practices and expectations from YouTube DPP. In short, when YouTube DPP helps predisposed type 2 diabetic and prediabetic populations improve their quality of preventive self-management and wellness in the overall patient care continuum, positive social change happens. According to Walden University (2021), positive social change is defined as any political, health educational, behavioral, social, psychological, medical, physical, or business practice that impacts society and the population towards positive and beneficial outcomes.

In this chapter, I provide a brief description of why online health related content is needed during the pandemic and how YouTube DPP could help reconnect the public to type 2 diabetes managed care. It explains why YouTube DPP are needed and how this type of programing could impact many people. This chapter also highlights relevant research supporting assumption, gaps in literary knowledge, and the next steps in research to remedy the issue. I briefly expand why I chose a nonexperimental, retrospective, cross-sectional approach for the study design and methodology, based on the research question. Finally, I briefly explain how the social cognitive theory (SCT) was used as the framework for the study, followed by a summary of the limitations and significance of conducting this study.

Background

Theorists like Madrigal and Mannan (2020) implied that YouTube could be leveraged to promote and advocate for better DPP enrollment and use online. More than

80% of the population watches YouTube, and research by Rangarajan et al. (2019) and Hasamnis et al. (2019) have shown the use of YouTube to be effective in presenting health information. Chapter 2 provides a comprehensive discussion on prior research and literary gaps in knowledge supporting the need for this study. This further supports the possibility of using DPP videos to reconnect patient populations to self-managed care in the lack of face-to-face consultation, especially during pandemics, like COVID-19.

Little is known about the general American adult population's PI of enrolling in YouTube DPP to promote better preventive and self-management of type 2 diabetes, especially since the COVID-19 social distancing mandate. Thus, additional research was needed to confirm and substantiate the correlation between COVID-19 SDC and the PI of enrolling in YouTube DPP. This study intended to assess if a relationship or a correlation existed between SDC levels and the PI of enrolling in YouTube DPP amongst participants.

This study explored if YouTube DPP videos were perceived by the online U.S. adult population as being significantly beneficial. Clinicians could potentially use YouTube DPP to improve type 2 diabetes education and self-management in the U.S. adult online predisposed population.

Problem Statement

Although evidence supported that DPPs were effective at improving diabetic health conditions when applied, in the past 5 years, research by Venkataramani et al. (2019) and Holliday et al. (2019) has shown that enrollment into these on-site DPP programs was low. Currently, only 1% of the diabetic population uses these programs, and even fewer were referred by a clinician or worksite (Ackermann et al., 2019; Holliday et al., 2019; Venkataramani et al., 2019). This meant that, even though preventive measures were being taken to reduce the incidence rate, type 2 diabetes continues to pose a threat to the patient care continuum, where one in three American adults are susceptible (CDC, 2021).

According to Healthy People 2030 (2020), there was little or no detectable change in the past 10 years for people with diabetes receiving consultation for monitoring their daily blood sugar levels. Now with COVID-19 social distancing mandates in place, isolating the public from basic medical consultation, it is assumed that even less of the target population will use on-site DPP due to fewer pre-diabetic screenings and referrals to on-site DPPs (Ackermann et al., 2019). Therefore, it is also assumed that the public is just not responding quickly enough to DPP promotions, or DPP are not responsive enough to the public (Cannon et al., 2020).

Prior evidence-based research indicated that YouTube was a very effective educational health literacy tool. Mensa-Wilmot et al. (2020), Madrigal and Mannan (2020), and Nye (2020) indicated that YouTube transcends health literacy and inequity issues concerning health awareness and education in vulnerable populations. Surely, harnessing online DPP on YouTube could prove advantageous to the discipline (Nye, 2020). Yet, more research is needed to substantiate the importance of enrolling in YouTube DPP videos in relation to SDC. So, in this study, I tried to quantify a statistically significant association between SDC and the PI of enrollment practices into YouTube DPP.

Purpose of the Study

There were low numbers of enrollment into DPP before COVID-19 social distancing mandates (Holliday et al., 2019). It is presumed that the pandemic escalated the need for YouTube DPP video programing to increase enrollment (Mensa-Wilmot et al., 2018; Ritchie, 2020; Plohl & Musil, 2021). Thus, identifying if there is an interest in YouTube DPP would provide the means for connecting the population to CDC accredited YouTube diabetes education and preventative self-managed programs during pandemic situations in the future (Mara & Peugh, 2020). I sought to identify if a relationship existed between social distance compliance levels and the importance of enrollment into YouTube DPP based on some common enrollment practices, like screening and referral campaigns. Results may shed some light on the attitudes of participants to help advocate and promote type 2 diabetic screenings and referral practices to increase enrollment into YouTube DPP because of the COVID-19 social distancing mandate.

Due to limited resources, such as interviewing consultations, funding, and time constraints, the study was conducted as a quantitative, non-experimental survey with a retrospective cross-sectional approach. The purpose was to assess if there was a correlation between the PI of YouTube DPP videos and COVID-19 SDC levels in the online U.S. adult population for future enrollment into and expectations of YouTube DPP. The study measured COVID-19 SDC levels and the PI of enrolling into nationally accredited YouTube DPP by online participants using a five-point Likert scale with an online survey instrument hosted on Survey Monkey.

Again, I assessed if there was a correlational relationship between SDC levels and the PI of enrolling in YouTube DPP for better type 2 diabetes self-management during the COVID-19 pandemic amongst online U.S. adult study participants. SDC levels represented the independent categorical variable used to denote the participant's compliance to government mandates and personal beliefs. For instance, SDC levels served as a response to observed environmental factors, like the social distancing mandates in place during the pandemic, and the participant's personal beliefs to comply to those mandates. This was associated with the dependent scalar variable, i.e., the PI of enrolling in YouTube DPP, as it pertains to the participants attitude towards enrollment practices and behavioral change expectations from getting formal diabetes education for better self-management during the COVID-19 pandemic (Mensa-Wilmot et al., 2020). The SCT framework for my study outlined behavioral expectations, or in this case, getting formal type 2 diabetes education for better self-management from enrolling in YouTube DPP, as the dependent variable based on the results of observed social distancing mandates (environmental factors) and personal beliefs concerning these mandates (personal factors). Further explanation concerning the variables in this study is given in Chapters 2 and 3. The purpose was to develop an understanding of the basic association between SDC and YouTube DPP to determine if there is a demand for such programming in the online community due to social distancing (Banerjee et al., 2020; Clark et al., 2020). It may motivate clinicians to implement better approaches to increase enrollment and engagement numbers in practice.

Research Question and Hypotheses

Research Question: Is there a statistically significant difference in the perceived importance of enrolling in YouTube DPP between COVID-19 social distancing compliance groups amongst survey participants?

Null Hypothesis: There is no statistically significant difference in the perceived importance of enrolling in YouTube DPP between COVID-19 social distancing compliance groups amongst survey participants.

Alternative Hypothesis: There is a statistically significant difference in the perceived importance of enrolling in YouTube DPP between COVID-19 social distancing compliance groups amongst survey participants.

The independent categorical variable was COVID-19 SDC and the PI of enrolling in YouTube DPP was the dependent scalar variable. The social distancing mandates for the COVID-19 pandemic have made face-to-face connections difficult for fostering patient-doctor relationships (Banerjee et al., 2020). Consequently, social media and online programming have become very advantageous in keeping patients connected to healthcare providers (Bavel et al., 2020; Kocyigit et al., 2020). Thus, the comparison of the PI of enrolling in YouTube DPP within SDC groups amongst participants from the online population was tested. The results were used to improve the body of knowledge concerning leveraging YouTube DPP for reducing the number of undiagnosed prediabetics and type 2 diabetics within the American adult population (Healthy People 2030, 2020). Measurements were based on a five-point Likert scale value system, where total value scores from 1 to 5 will be compiled and compared (McLeod, 2019). For example, (1) represented the minimum value and (5) represented the maximum value on the five-point scale (McLeod, 2019). The value system and scores used to measure these two variables depicted the attitudes and perceptions of the online survey participants towards SDC and enrollment into YouTube DPP for getting formal type 2 diabetes education for better self-management in a COVID-19 pandemic climate. Please note that this is expanded on in Chapter 2.

Theoretical and/or Conceptual Framework

The SCT was used in this study as a framework. The theory originated in the 1960s by Bandura and Walters for learning education (Sharma, 2021; Wulfert, 2019). In 1986, Bandura further developed the theory into what is commonly used today in behavioral health. The theory consists of three major constructs that help behavioral health practitioners identify personality or behavioral intent based on observed environmental factors (social norms) impacting an individual's attitude or preconceived beliefs, i.e., personal factors (Shamizadeh et al., 2019; Zhou et al., 2020). Although the theory is used to identify and understand attitudes, it cannot be used to change behavior, just identify the potential that already exists (Sharma, 2021). Since the goal of the research question was a comparison of different attitudes within groups, the SCT was effective in determining participant attitudes to make statistical associations relevant to behavioral intent.

In short, this study used the SCT, first developed by Bandura in 1986, to understand perceptions towards enrolling in YouTube DPP, in response to COVID-19 SDC (Sharma, 2021). Thus, SDC represented the environmental factor and personal factor in the SCT framework and the PI of enrolling in YouTube DPP will represent the behavioral component. To clarify, the two constructs (environmental and personal factors) of SDC, the independent variable in the framework, gave rise to the desired behavior, the PI of enrolling in YouTube DPP based on common recruitment practices and expectations of getting formal diabetes education for better self-management, i.e., the dependent variable (Shamizadeh et al., 2019). Chapter 2 expands on the SCT further, in addition to examining the assumption associated with its use to motivate or promote behavioral expectations of enrollment into YouTube DPP within the U.S. online adult population due to COVID-19 social distancing practices (Zhou et al., 2020).

The framework related to my research problem by examining the need for more YouTube DPP. The SCT framework related to the purpose of the study by highlighting concerns and attitudes which prevent and motivate enrollment into YouTube DPP, using environmental and personal factors, due to the COVID-19 pandemic. The framework related to the nature of the quantitative survey by examining perceptions and attitudes correlating to the enrollment into YouTube DPP, in response to survey participants' COVID-19 social distancing practices.

Nature of the Study

In experimental studies, researchers use random selection for both experimental and control groups (Mohebbi et al., 2019). Without access to unique candidates to designate into control and experimental groups, I selected a nonexperimental study. This study was quantitative in nature, with a retrospective, cross-sectional approach. Nonexperimental studies like this use closed or open ended, self-reporting surveys and are commonly used to describe and correlate variables based on an observed phenomenon (Mohebbi et al., 2019). In this case, data were collected using a closed-ended question survey at one point in time about an observed phenomenon, i.e., COVID-19 SDC in retrospect, as it correlates to participants PI of enrolling in YouTube DPP videos. This study was observational in nature, intended to uncover the attitudes and beliefs of participants and correlate those ideals with behavior (Sharma, 2021). Therefore, interviewing the participants was required to answer the research question. Quantitative self-reporting questionnaires allowed me to conduct the interview using limited resources without hiring an interviewer (Mara & Peugh, 2020). Closed-ended question survey instruments have limits. For instance, I was limited to the type of questions asked and the responses participants gave (Sharma, 2021). Yet, the data were easier to analyze than open-ended survey instruments when faced with short time frames (Querido et al., 2021). In addition, the SCT is readily used in research, so incorporating it into the study as a framework to assess the attitudes and perceptions of participants would be easier to replicate and more familiar with research clinicians (Guerrero, 2018). So, with limited time and resources at my disposal, a probabilistic nonexperimental, cross sectional, close-ended, self-reporting questionnaire worked out best for achieving my research goals. More about the nature of the study design paradigm is discussed in Chapter 3.

To address the research questions in this quantitative study, IBM SPSS Statistical software version 28 was used to quantify the specific nature of the relationship between COVID-19 SDC and PI of enrolling in YouTube DPP (IBM, n.d.). Social distance compliance represented the independent variable of the study. It represented what the participant population believed to be their compliance level during the COVID-19 pandemic. The variable also represented the participants' ideals associated with the societal norms coinciding with the social mandates in place for COVID-19. The dependent variable for this study was the PI of enrolling in YouTube DPPs. The dependent variable exemplified recruitment, like screening and referrals efforts, as those elements apply to the importance of enrolling in YouTube DPPs (Holliday et al., 2019). Finding an association between those two variables helped redefine the practice when it came to promoting online type 2 diabetic wellness programs. When analyzing the two variables, age, sex, health status, and education levels could be considered as covariates (IBM, n.d.). Those factors may falsely increase the compliance levels and the PI of enrolling in YouTube DPP during the pandemic, since older adults with college education tend to pay more attention to health and wellness.

This was a quantitative cross-sectional study that was conducted for weeks. The SurveyMonkey platform generally has analytics such as tabulated responses to each answered question, the numbers of total participants, the length of time responding to each question, and the number of visits per participant (SurveyMonkey, n.d.). Participants were selected from online social networking groups such as Facebook. Participation in the study consisted of adults over the age of 18 and excluded pregnant women. The selection represented the general adult population defined in the Healthy People 2030 (2019) guidelines for American adults predisposed to type 2 diabetes. The sample size was calculated based on the target population size, the power, and effect size of the one-way analysis of variance (ANOVA) for the study. More explanation concerning sample size selection and participant recruitment is given in Chapter 3.

Data collection was accomplished using instrumentation and operations consistent with well-known survey instruments utilizing a Likert Scale (Querido et al., 2021). The selected instrument for this study was a quantitative close-ended questionnaire, and the survey tool elicited responses by asking a series of closed-ended questions. Thus, measurements were based on the operations of a 5-point Likert scale, where 1 was the lowest response value and 5 was the highest response value (McLeod, 2019). The instrument measured the PI of enrolling in YouTube DPP videos, where, on the 5-point scale, 1 = not important and 5 = absolutely important. The instrument also measured social distance compliance levels, where 1 = never and 5 = always. The validity of the survey tool was confirmed using Cronbach's alpha coefficients, which will also be discussed in depth in Chapter 3 (Tsang et al., 2017).

IBM SPSS statistical software version 28 was used to analyze the data collected once uploaded from SurveyMonkey. First, descriptive statistics were used to analyze the theoretical constructs of the SCT for PI of enrolling in YouTube DPP and social distance compliance levels (Querido et al., 2021). Social distance compliance levels were categorized into five groups, i.e., noncompliant, low compliance, compliant, highly compliant, and always compliant, in which the PI of enrolling in YouTube DPP was determined within each group. P-values greater than 0.05 were indicative of no statistical relevance in mean differences within categories and between groups (Leppink & Pérez-Fuster, 2017). Then an analysis of variance (ANOVA) was conducted to answer the research question and hypothesis. Further analysis and derivations (like from the Chi-square) were used to base results on, but these matters are discussed in Chapter 3, as well.

Definitions

The following are concise definitions of key terms and phrases used throughout the study.

Activities or program activities: This refers to the belief by participants that program content will easily integrate into their daily lives to help them achieve better control and self-management of diabetes.

Basic enrollment assumptions: This refers to the assumed benefits and conditions of enrolling into YouTube DPP identified by clinicians, insurance companies, researchers of prior evidence-based studies, the CDC, and the American Diabetes Association.

Behavioral expectations, behavioral outcomes, or behavioral change: Bandura (1986) defined this as the plausible behavioral result or expectation based on environmental factors and personal factors.

Commitments or commitment practices: This refers to keeping up with the program requirements to get the expected results. This is defined by Bandura (1986) as the behavioral outcome or behavioral change due to environmental factors and personal factors.

Diabetes Prevention Programs (DPP): Albright et al. (2020) and Beck et al. (2017) stated that programs should be nationally validated and communicate preventive and self-managed type 2 diabetes care regiments. In addition, a program can be an on-site face-to-face program, a live webcam, or an online video (CDC, 2020).

Enrollment, enrolling, or enrollment process: This refers to common recruitment practices for engaging in YouTube DPP towards positive social change.

Environmental factors: Bandura (1986) defined these as the learning observations and social norms that influence behavioral outcomes.

Expectations: This refers to acknowledging the potential benefit of getting formal diabetes education for better self-management from enrolling in YouTube DPP during the COVID-19 pandemic amongst the online U.S. adult study participant population. It is the anticipation that participants will witness meaningful results within a reasonable period of time due to keeping the commitments and doing the activities outlined in the YouTube DPP.

Favorability score: This is synonymous to the PI of enrolling in YouTube DPP.

Government mandates: The basic policies in place by the CDC (2019) during the COVID-19 pandemic to keep communities safe and stop the spread of the disease.

Perceived importance (PI): This refers to how important enrolling into YouTube DPP is to participants based on common enrollment practices (i.e., referrals and screenings), basic enrollment assumptions, and the activities and commitments imposed by YouTube DPP. PI is a dependent (scalar) variable which will be scored on a five-point Liker scale, where 1 = Not Important, 2 = Little Importance, 3 = Important, 4 = Very Important, and 5 = Absolutely Important.

Personal factors: Bandura (1986) defined these as the personal attitudes, motivation, beliefs, ideals, and self-efficacy that influences individual behavioral outcomes.

Personal measures: These are actions participants take to keep themselves or families safe and protected from COVID-19

Positive social change: It is the exhibited behavioral outcomes by individuals and communities that impact society in positive ways from the influence of clinical, social, or business practices and evidence-based research, according to Walden University (2021).

Recruitment practices: This encompasses common referral, screening, and enrollment processes, tools, marketing strategies, campaigns, and promotions used to actively enlist qualified candidates into YouTube DPP.

Referral: This refers to common referral practices used to influence candidates to make better health decisions by enrolling in DPP.

Screening: This refers to common eligibility criteria in practice for enrollment into YouTube DPP.

Social cognitive theory (SCT): This refers to Bandura's (1986) learning theory comprising social norms and individual attitudes that influence behavioral outcomes.

Social cognitive theory constructs: This is the integration of Bandura's (1986) SCT into the study with the SDC representing the environmental and personal factors and the PI representing the behavioral outcome in the framework.

Social distancing compliance, or social distance compliance (SDC), SDC groups, or SDC level(s): This refers to compliance behavior participants applied during the lock down mandate or continues to apply throughout the COVID-19 pandemic. This is the independent (categorical) variable, which was categorized into five groups (Noncompliant, Low Compliance, Compliant, Highly Compliant, and Always Compliant) based on government mandates and personal measures. The variable was measured on a five-point Likert scale, where 1 = Never, 2 = Rarely, 3 = Sometimes, 4 = Often, and 5 = Always.

U.S. adult online community: This is the Healthy People 2030 (2020) definition of the U.S. prediabetic and type 2 diabetic adult population excluding pregnant women and individuals under 18 years old.

Please note that more details about coding and further use of these terms will be provided throughout this and the remaining chapters.

Assumptions

According to Hasamnis and Patil (2019), it is a general assumption that the online community represents the general population. According to Mondal and Mondal (2020), the online population has a need for health-related content due to COVID-19 social distancing. The other assumption is that there is a considerable increase of importance of health-related information because of social distancing (De Silva et al, 2020; Mensa-Wilmot et al, 2018; Nye, 2020). Haslam et al (2019) indicated how YouTube video content helped direct healthier decision making within participant populations despite health literacy issues within disadvantaged populations. The other assumption that Devendorf et al. (2020) expanded on is that the public would like to know and have this information, however, they believe that it is inaccessible to them (i.e., information that they probably do not have access to or can obtain).

The assumptions mentioned by De Silva et al (2020), Nye (2020), and Mensa-Wilmot et al (2018) are important because they support the need for my study. In addition, the social cognitive framework can be easily adapted and generalized to accommodate my design and methodology for the study based on these assumptions. In short, without these assumptions, it would be difficult to validate a need for conducting my study and formulating differential or analytical statistics.

Scope and Delimitations

Clinicians believe that patients need and want to engage in YouTube DPP because the programs communicate vital information for better diabetes self-management during the COVID-19 pandemic (Clark et al., 2020). However, these are only assumptions made based on research findings, as outlined by Clark et al. (2020) and Devendorf et al. (2020). These assumptions support the importance of enrolling in YouTube DPP to the public, or the people in which these programs are supposed to benefit during the pandemic. According to Healthy People 2030 (2020), there is no percent baseline for whether the public perceives YouTube DPP as important or beneficial to them during the pandemic or otherwise. It is just assumed that that is the case because the safety and health concerns of the diabetic population is important to clinicians (Nigg et al., 2021; Yanti et al., 2020). Yet, the population may not perceive enrolling in YouTube DPP as important or beneficial to them during the pandemic (Zhou et al., 2020). It is unknown if the recruitment process which clinicians use to enroll candidates into YouTube DPP are perceived as important (Li et al., 2020; Zhou et al., 2020). So, I attempted to identify if the online community believes that enrolling in YouTube DPP during the pandemic to be beneficial for them by evaluating participants’ attitudes towards common recruitment practices and behavioral expectations. I tried to determine if individuals perceive program commitments and activities outlined during enrollment into YouTube DPP were important motivators for enrolling in YouTube DPP during the pandemic.

Another assumption is that Mensa-Wilmot et al. (2018) and Haslam et al. (2019) both claimed that the YouTube recommendation system may be more effective than the referral process currently used in practice and is worth investigating. In addition, Mohebbi et al. (2019) credited the health belief model (HBM) for being more responsive at identifying behavioral triggers and making predictions about unique behavioral diabetic self-management trends within participant populations than the SCT, which in my study only identified participant attitudes and perceptions. Also, assessing type 2 diabetic and prediabetic participants at different ages that frequent the internet opposed to those that do not (concerning compliance and PI) would be another appropriate investigation. Assessing type 2 diabetic and prediabetic participants with YouTube subscriptions, opposed to those that do not have a subscription, would be another example of the HBM in action using the Mohebbi et al. strategy. Any of these investigations would add to the external validity of my study and the practice. Yet, with limited resources and time restrictions, investigating these assumptions were beyond the scope of this study, and the SCT framework was most appropriate for defining the attitudes and perceptions of the participants from the online community (Lin et al., 2020; Sharma, 2021).

This study was generalized in that the participant pool represents the U.S. population, which was susceptible to type 2 diabetes, i.e., one in three U.S. adults may have prediabetes (CDC, 2020). Pregnant women and minors were excluded because they did not represent the adult population criteria outlined in the Healthy People 2030 (2020). The study aimed to identify the online population's attitudes and propose ways to improve the practice towards better diabetic self-management (Lin et al., 2020; Sharma, 2021).

Limitations

The SCT framework is designed to identify the beliefs and attitudes of participants experiencing environmental events, or conditions. Bandura (1986) introduced the theory to understand the learning process. For this experiment, the theory was not meant to make predictions or formulate causations, but simply identify PI or observe what participants believe at a particular time, which was appropriate for my study. However, people may forget and do not reflect past events in real time. They may have broken memories and fractured recollections of what happened. This could distort the results when it comes to interpreting emotions and attitudes. However, studies have shown that the surveyed population answers questions to their best ability, as truthfully as possible. So, the most effective way of addressing these biases was to ask multiple questions about the same topic or have the same line of questioning. According to Mellinger and Hanson (2020) and Bolarinwa (n.d.), providing participants with multiple questions about the same topic allows participants to cognitively process their thoughts to minimize their biased response.

Since the study questionnaire was close-ended and self-reporting, I was limited to providing participants with concise statements and/or questions with a narrow response to choose from, as required for a quantitative study, as opposed to open-ended questions that would be used in a qualitative study. Therefore, I used validated survey instruments to tailor my research questionnaire. According to Tsang et al. (2017), Mellinger and Hanson (2020), and the National Business Research Institute (2021), using validated questions from well-established survey instruments improved the internal validity of my study and provided me with credible questions and responses for reliable results.

Significance

Since the U.S. population experiences further isolation from the medical community due to the COVID-19 pandemic, there is a need for online health related content to reconnect the public. Although the importance of enrolling in YouTube DPP is assumed to be of some significance to the public, little research has been conducted to validate the claim that the public perceive enrolling in YouTube DPP as significant. This study intended to answer if the online U.S. population views enrollment in YouTube DPP as beneficial during the COVID-19 pandemic in response to their individual SDC levels. The study would increase the understanding of the PI of these types of programs on YouTube and whether the online community finds them beneficial during crises, such as pandemics.

In addition, my research may improve the enrollment strategies in practice and the quantity and quality of YouTube DPP. According to Mensa-Wilmot et al (2018), clinicians must be able to recognize basic concerns within the general population to address low diabetic screening rates and increase enrollment into DPP. Therefore, understanding the general population’s PI of enrolling in YouTube DPP may shed some light on issues regarding low diabetic screening rates and improve enrollment into these programs, if the online population deemed enrolling into these programs as beneficial (Ackermann et al., 2019; Barry et al., 2017; Mensa-Wilmot et al., 2020). For instance, the study may indicate areas in the enrollment process where the online community loses interest or where interest is the highest for onboarding new participants.

According to Walden University (n.d.), positive social change is the ability to impact behavioral outcomes for positive health and wellness lifestyles. The assumption is that after engaging in specific actions outlined in the YouTube DPP, individuals should become more capable of self-managing their type 2 diabetes and insulin, to improve their overall health. It is my hope that the results of my study would lead to possible solutions to help lower the incident rates for type 2 diabetes and will increase the number of people who know about preventing and managing type 2 diabetes, including how to manage their insulin daily. Doing so would help achieve the Healthy People 2030 (2020) initiative, where more than 52% of the U.S. population will know if they have type 2 diabetes and at least 50% of diabetic patients improve on taking their insulin daily. For this to happen, clinicians must understand the importance that the online community places on enrollment into YouTube DPP and the screening/enrollment process throughout this pandemic. In short, clinicians must understand how to improve the low enrollment rates into these programs. The study answered if there was a statistically significant difference between SDC groups (which was measured by assessing compliance to government mandates) and the participants' PI of enrolling in YouTube DPP, as this specifically related to the PI of common screening and referral practices, along with some basic program commitments and activities. Hopefully, my study may help reinforce the need for better recruitment practices for enrollment into YouTube DPP.

Summary

In response to COVID-19 social distancing practices, the SCT was used to help determine the population's PI of enrolling in YouTube DPPs as one possible solution for improving enrollment rates for YouTube DPP. Study results may help foster positive social change by identifying beliefs and highlighting attitudes towards enrolling in YouTube DPP during the COVID-19 pandemic, as observed by Mensa-Wilmot et al (2018) and Madrigal and Mannan (2020). Chapter 2 expands on the literary gaps and the theoretical framework that reflect the foundations of the study. I also discuss common assumptions, the key variables, and the selection criteria used to add credibility to my study.

Chapter 2: Literature Review

Prediabetes is prevalent and using DPP remains the best way to promote diabetes awareness and educate the U.S. adult population (Centers for Disease Control and Prevention, 2020). However, low screening and enrollment rates indicates that DPP are not being used to the fullest (Ackermann et al., 2019; Apolzan et al., 2019; Cannon et al., 2020). Screening individuals for enrollment into the program has become more difficult because of the COVID-19 pandemic (Calo et al., 2020). Clinicians do not have a baseline for the percentage of the U.S. population that perceive enrolling in online YouTube DPP as important tools for getting formal diabetes education and self-management during the COVID-19 pandemic (Healthy People 2030, 2020). According to Healthy People 2030 (2020), establishing the baseline for low enrollment and completion rates in type 2 DPP recognized by the CDC are of high priority—D-D01. In addition, there was little or no change in 50% of the diagnosed diabetic population, from 2017 to 2020, who received formal diabetic education—D-06. Currently, one in three U.S. adults are prediabetic and do not know—D-02 and about 20% of the diabetic population are not monitoring insulin correctly to control type 2 diabetes daily—D-07 (Healthy People 2030, 2020). Therefore, this study explored the assumption that individuals who are compliant will be more willing to enrolling in online YouTube DPP to get formal diabetes education for better self-management to bridge the communication gap with the healthcare community (Al-Hasan et al., 2020; Plohl & Musil, 2021; Xie et al., 2020).

I developed a literary search strategy to evaluate key variables in the research question based on major SCT constructs. Strategies entailed searching databases using groups of terms related to specified selection criteria from articles published within the last 5 years. The selected articles were analyzed for gaps in the literature and the relevance of using SCT as the theoretical framework to expand study assumptions.

In this chapter, the literature review is analyzed to validate the rationale for selecting the SCT and associated assumptions as the theoretical framework. Then, I expand on environmental factors, personal factors, and the behavioral outcomes based on observational learning and self-efficacy as described in the SCT. Finally, the significance of using the SCT in relation to the research question is addressed.

For the key variable section, information highlighting DPP will be discussed as well as the scope of the problem in terms of screening for enrollment issues into the national DPP. The information gathered focused on problem solving and using YouTube DPP as a promotional awareness and evaluation tool for conveying common information about type 2 diabetes prevention during the COVID-19 pandemic. This section assesses controversies as well as the gaps in literature concerning the key variables and centered on the reasons for selecting the key variables.

Literature Search Strategy

First Phase: Term Search

There were two phases in the search strategy process for article selection, i.e., the term search and article categorization. The first phase, outlined in Table 1, consisted of five different key term group searches, where credible literature was selected from well-known databases. Articles selected from Group 1 terms outlined in Table 1 provided information about the premise of the study from a health education and promotion perspective, while the peer review articles selected from term Group 2 provided information to better understand the use of metformin therapy in DPP, the effectiveness of regulatory practices in the implementation process of DPP, and the standards of operations undermining DPP enrollment rates. Prediabetes and prediabetes commercial were the key terms used in the third group search found in Table 1, which provided information for assessing relevant health related content on risk testing, prediabetes screening, and resource availability and awareness published on YouTube. The fourth term search provided information on risk factors and screening, while the fifth term search provided information about the gaps in the literature and the theoretical framework for conducting a credible study.

Table 1

First Phase: Database Term Search of Peer-Reviewed Articles

	1	2	3	4	5
Search years	2014-2021	2016-2021	2016-2021	2019-2021	2016-2021
Multi-Databases	Google Scholar, Elsevier, CDC.gov, SAGE, and American Diabetes Association	Google Scholar, Elsevier, CDC.gov, SAGE, and American Diabetes Association	YouTube	Google Scholar, ProQuest, PubMed, and MEDLINE	Walden University Library, Thoreau, EBSCO, Taylor & Francis, and ERIC
Key term(s) searched	YouTube, referrals, and (DPP)	Diffusion of innovation and DPP, DDP site locations, insurance	Prediabetes commercial	Prediabetes risk factors, prediabetic screening,	YouTube education, and health

		coverage and cost, diabetes program enrollment rates, implementation of diabetes program, Metformin therapy, BMI, obesity, and HbA1C levels		YouTube	
Results	13,300	11,600	>200	612	104
Relevance of search	Search for health education, health promotion perspective	Dissemination and enrollment rates, effectiveness, and use of metformin therapy for comparison	Diabetes risk testing, prediabetes screening, and resources	Risk factors and screening	Validity and reliability in research, research gaps, and the SCT framework

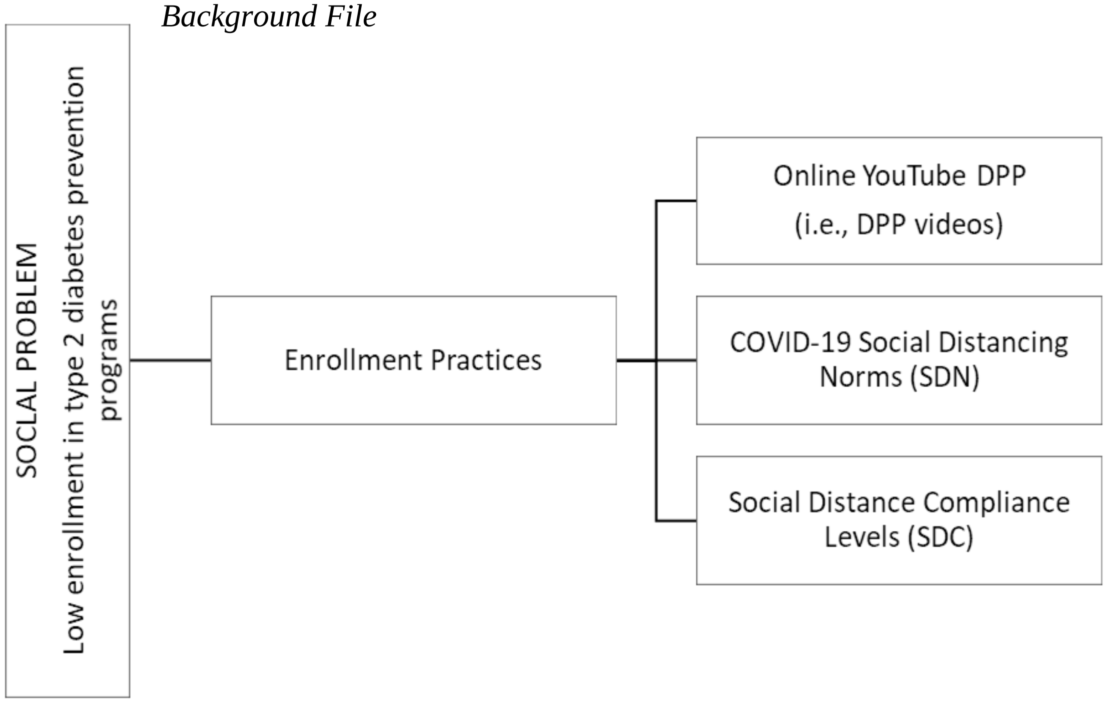
Note. This table provides a basic summary of the terms searched in Google Scholar, Walden University Library, and other multi-databases. DPP = diabetes prevention programs; CDC = Centers for Disease Control and Prevention; BMI = basic metabolic index; HbA1C = Hemoglobin A1C; SCT = Social cognitive theory.

Second Phase: Article Categorization

I compiled a list of relevant peer reviewed articles from the first phase of article selection in Zotero, a dedicated reference management software by Corporation for Digital Scholarship (n.d.). Articles older than 5 years were removed from the list and not used. I created three categorical files in Zotero, i.e., Background information, Literature Gap, and Framework, to support the premise of the study. In this case, the correlation between the PI of enrolling in online YouTube DPP in response to SDC in the U.S. adult population. Thus, background information, presented in Figure 1, entailed relevant evidenced based material substantiating the prevalence of prediabetes and type 2 diabetes in the United States as a social problem and the DPP initiative as a failing national solution, due to poor screening and enrollment practices (Malone & Hansen, 2019). Concerns about the negative and positive impact of the COVID-19 pandemic and SDC on DPP screening for enrollment practices were also incorporated into the Background File seen in Figure 1. Articles proposing YouTube as a viable recommendation for improving DPP screening practices for positive social change were selected for the Background information file as well (see Figure 1). Articles that illustrated theoretical propositions relating to the SCT were selected for the SCT Framework File represented in Figure 2. The contextual information, i.e., correlating social distancing as an environmental factor, and individual compliance levels as the personal belief factor, with the PI of enrolling in online YouTube DPP as the response to both the environmental and personal belief factors, alluded to in the SCT (see Figure 2). The evidence in the selected articles illustrated the theoretical dynamics of the problem in terms of SDC levels and the key to utilizing online YouTube DPP on YouTube. Finally, articles that demonstrated a need for more research, or the inability of the research to determine if there was PI placed on online YouTube health related information video content, like YouTube DPP videos, during the COVID-19 pandemic, were selected for the Literature Gap File presented in Figure 3. In addition, articles that indicated a lack of evidence identifying a PI enrolling in online YouTube health related information videos due to individual SDC behaviors and beliefs were also placed into this file (see Figure 3). However, articles that mentioned pregnant women, children, or adolescence as viewers were excluded, since these individuals were primarily excluded from the U.S. adult target population (see Figure 3).

Figure 1

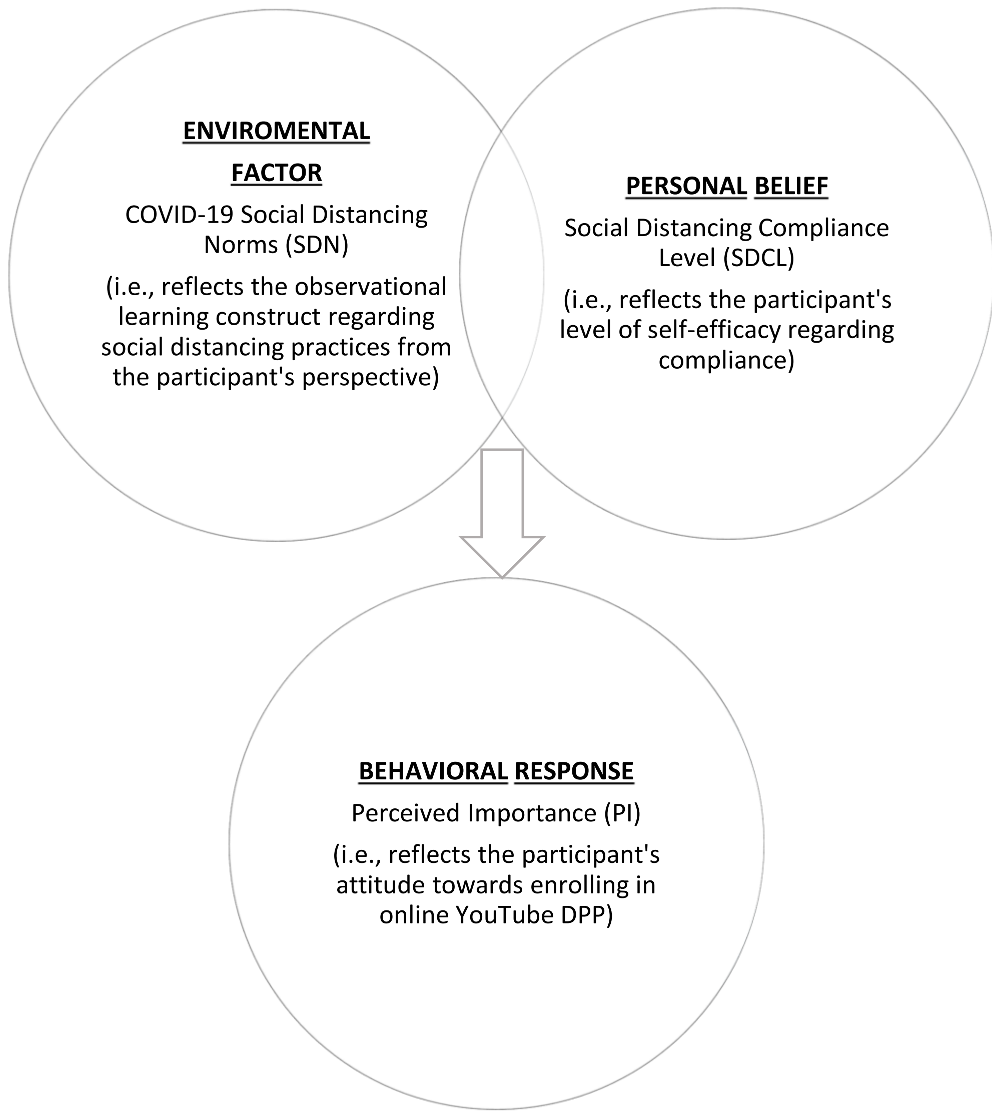
Background File



Note. Articles categorized in Zotero based on background content needed for literature review.

Figure 2

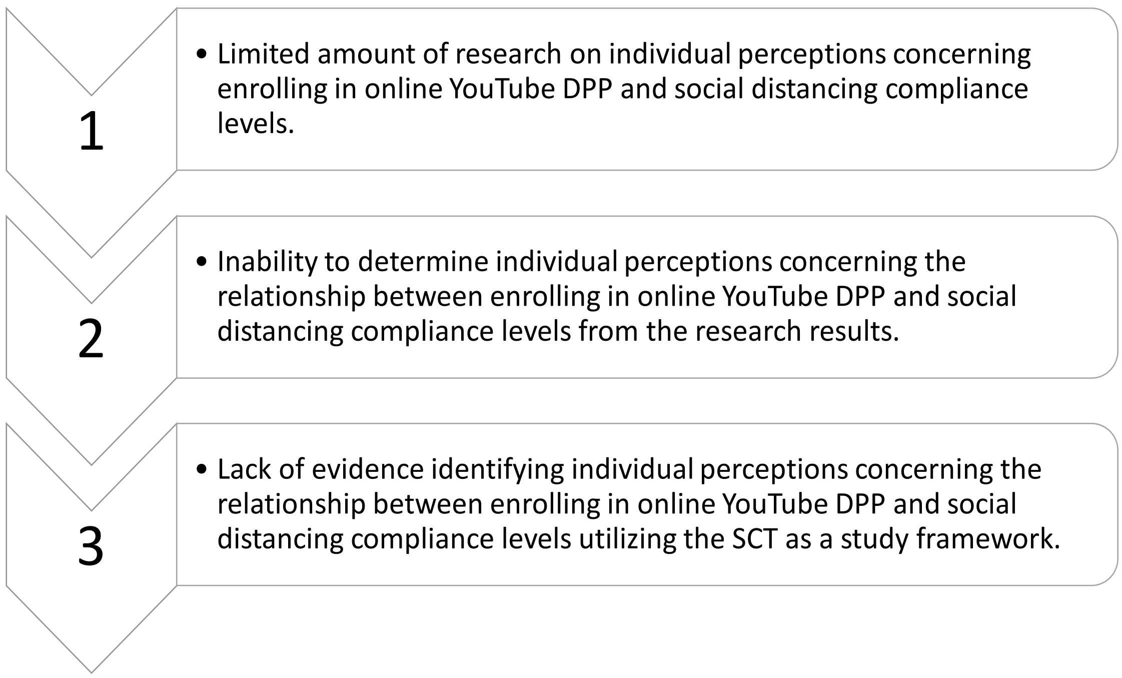
SCT Framework File



Note. Articles were sorted into categories in Zotero based on SCT environmental factors, personal beliefs, and behavioral responses relevant for literature review.

Figure 3

Literature Gap File



Note. Article were categorized in Zotero according to specified literature gap criteria.

Thus, a literary search was devised to find relevant peer reviewed articles to highlight the current social change implications of using national YouTube DPP videos in relation to the scope of the study, i.e., COVID-19 SDC and the significance of enrolling in online YouTube DPP in the online community. The focus of the search was confined to social distancing, compliance, and YouTube health related information videos, like YouTube DPP videos. Whether the application of YouTube DPP videos increased screening and enrollment rates into national DPP was not assessed at this time, due to the limited amount of data found.

Theoretical Foundation

SCT as a Theoretical Framework

A literary assessment underlining the theoretical constructs of the SCT as it relates to the propositions and assumptions appropriate for this study was conducted and the results summarized in the proceeding paragraphs. The SCT was used in this study as a theoretical framework to understand perceptions of the general adult population towards enrolling in online YouTube DPP, in response to COVID-19 social distancing (Sharma, 2021). The SCT, proposed by Bandura in 1986, was first developed by Bandura as the social learning theory in 1977 (Bandura, 1986). The SCT outlines "psychological processes that govern human behavior," according to Wulfert (2019). The framework predicts, models, and examines perceptions of a given behavior by identifying the behavior and the determinant factors in the decision-making process that govern the behavior (Sharma, 2021; Wulfert, 2019).

Constructs of the SCT

Researchers use the SCT, which uses internal and external determinant factors in the decision-making process, to understand the development, sustainability, and adaptation of a specific behavior (Sharma, 2021; Vergeld et al., 2020). Internal determinants constitute the thoughts, expectations, and belief systems that an individual possess and represents the cognition or personal factors in the framework (Shamizadeh et al., 2019). External determinants, or environmental factors, refer to the consequential punishment received, or reward given to an individual based on the action that the individual has taken in response to the decision-making process and environmental factors the individual faced (Wulfert, 2019). The past experiences of adults, referred to as cognitive mediators, regulate and guide the decision-making process of behaviors (Xie et al., 2020). Additionally, language and images fortify the symbolic self-regulatory process for mental codes used to formulate cognitive resolutions and solve problems (Bandura, 1986; Xie et al., 2020).

Observational Learning Defined in the SCT

A major theoretical proposition emphasized by Bandura's SCT asserts that individuals possess the ability to control their own actions, to an extent (Wulfert, 2019). Individuals were not entirely passive, as behaviorists imply, when it came to environmental factors impacting their lives (Vergeld et al., 2020). Nor were individuals entirely "free agents" in response to environmental factors as humanists and existentialists would imply Bandura (1986) asserts. In addition, Brahman (1986) claimed that behavior originated from observational learning of language and imagery (Nigg et al., 2021; Wulfert, 2019). In short, people watched other people and observed the outcomes of the other people's actions to guide their own future behaviors (Vergeld et al., 2020; Shamizadeh et al., 2019). Gaining mastery of complex behaviors, such as speaking, reading, and writing a language was learned by individuals listening, watching, and imitating other people (Bandura, 1986; Nigg et al., 2021; Xie et al., 2020).

Self-Efficacy Defined in the SCT

The most profound assumption emphasizes self-efficacy as the most important determinate factor in the decision-making process (Wulfert, 2019; Vergeld et al., 2020). Self-efficacy was defined by Bandura (1986) as the ability of an individual to perform a given task or behave in a certain manner based on the belief that the individual possessed the ability and had the available resources to carry out the task or behavior. Self-efficacy lends itself to the internal thought process and invokes emotions that aim to aid or hinder internal cognitive mediators needed to motivate positive affirmations and bring about the proposed outcome (Yanti et al., 2020). Bandura advocates that people would be able to increase their levels of self-efficacy by mastering complex or difficult tasks. Exposing individuals to people like themselves who have performed difficult tasks would also increase the individual's self-efficacy (Wulfert, 2019; Vergeld et al., 2020). Being given the confidence through positive affirmations encourage self-efficacy, as well as, being given coping strategies to keep individuals calm when conducting difficult tasks is another way to promote self-efficacy (Al-Hasan et al., 2020; Vergeld et al., 2020). Thus, the SCT was previously deployed for identifying perceptions towards a behavior and predicting behaviors based on modeling or the observance of past behaviors.

Rationale for Selecting SCT Framework

Authors like Hasamnis and Patil (2019), De Silva et al (2020), Nye (2020), and Mensa-Wilmot et al (2018) contributed to the proposed study by predicating the research assumptions concerning COVID-19 SDC and the importance of observational learning through enrollment into online YouTube DPP as highlighted in the SCT. Mondal and Mondal (2020) used COVID-19 social distancing practices to expand on the need for online YouTube DPP as an observational learning tool. Haslam et al (2019) indicated how online YouTube DPP content helped direct healthier decision-making within participant populations despite health literacy issues within disadvantaged populations.

Thus, the SCT framework embodied the essence of environmental, personal, and behavioral factors expanded on in this study to explain the possible correlation between COVID-19 social distancing practices and the PI of enrolling in online YouTube DPP within the general adult population in the U.S.

Significance of SCT for the Study

In this study, social distancing represents the environmental factor and compliance represents a personal factor in the SCT framework used in this study (Bandura, 1986). These two factors i.e., environmental factors and personal factors in the framework, give rise to the desired behavioral change, i.e., enrolling in online YouTube DPP videos (Nigg et al., 2021; Shamizadeh et al., 2019). The behavioral change in favor of enrolling in online YouTube DPP due to an environmental factor, like the implementation of COVID -19 social distancing and a personal factor, like compliance to social distancing based on self-efficacy, observational learning, and expectations, may increase participant interaction with online diabetes self-management content (Bandura, 1986; Nigg et al., 2021). Thus, based on the SCT, COVID-19 social distancing practices could be associated with changing behavioral factors to accommodate the new social climate, prompting new behavioral acceptance of enrolling in online YouTube DPP within populations (Nigg et al., 2021; Xie et al., 2020).

The Research Question in Relation to the SCT

The framework related to the research problem, by examining the need for more online YouTube DPP. The SCT framework related to the purpose of the study by highlighting concerns and attitudes which prevent and motivate diabetic screening for enrollment into YouTube DPP, using environmental factors, like observed social distancing, due to the COVID-19 pandemic (Nigg et al., 2021). The framework related to the nature of the quantitative survey by examining perceptions and increased acceptance towards enrolling in online YouTube DPP, in response to COVID-19 social distancing practices (Bavel et al., 2020; Zajenkowski et al., 2020).

Key Variable Literature Review

Diabetes Prevention Programs (DPP)

More people are being diagnosed with diabetes now than ever before and 1 in 3 adults in the general population may have prediabetes (American Diabetes Association, 2020; CDC, 2020). This represents more than 80 million adults in the United States (CDC, 2020). With such astonishing numbers, there must be a national solution (Centers for Disease Control and Prevention, 2020). Apolzan et al. (2019) highlighted successful outcomes from implementing DPPs in a randomized study which followed participants in vulnerable populations diagnosed with prediabetes and type 2 diabetes. The methodology and study designs were complex, where three different groups were observed for 15 years to validate the significant role of DPP in self-managing diabetes. Azar et al. (2019) indicated that it is more pragmatic and less expensive to focus on a national solution utilizing DPP than resorting to drug therapy. Azar et al. (2019) focused on implementing or integrating DPP into healthcare systems based on the efforts of a large-scale diabetes health management program in North Carolina. Qualitative assessments were conducted based on that integrated health system and revealed gaps in clinician referrals, adoption practices, and collaboration among diverse teams in various disciplines within the health system (Azar et al., 2019). In short, DPP provides a way in which information concerning diabetes self-management can be relayed to the public. Mixed study methods highlighted the acceptability, adoption, appropriateness, cost, feasibility, fidelity, penetration, and sustainability of DPP (Azar et al., 2019). Evidence-based research studies identified the scope for supporting DPP through data collection methods, database resources, and the time frames for collecting relevant data, i.e., supporting this study design construct as an experimental survey to obtain accurate and current data to add to the body of knowledge concerning DPP (Apolzan et al., 2019). However, implementing these programs are not so promising when it comes to participant screening, referrals, and enrollment into the program.

Screening, Referrals, and Enrollment Issues

Screening

Results from the literature indicated that screening and reimbursement efforts for DPP from health insurers and practitioners were not as effective as believed. Less than 10% of the health risk population were identified through screenings, and only about 30% of those referred to DPP enrolled and participated in the program with positive outcomes (Ackermann et al., 2019). The results supported the need for better screening strategies for DPP as outlined in the HealthPeople2030 provisions to reduce the prevalence of type 2 diabetes in the U.S. adult population.

Referrals

Doctor referrals to DPP were correlated with participation rates in DPP. Venkatarmani et al (2019) used a conceptual framework to outline participants' interest in DPPs after being referred to the program from doctors. While 30% of those who participated in the study reported being referred by doctors, less than 2.5% participated after being referred (Venkataramani et al., 2019). The study confirmed the need to increase referral strategies, where less than 2.5% of respondents were referred and even fewer were interested in participating in DPP (Venkataramani et al., 2019). Thus, this evidence indicated the significance for future research to expand on referral strategies and add to the body of knowledge.

Enrollment

Evidence also demonstrated the need to expand insurance coverage (i.e., a major screening criterion for enrollment consideration into any national DPP) to increase enrollment numbers into DPP (Ritchie et al., 2019; Yin et al., 2020). In addition, the results of Holliday's et al (2019) study indicated that over 5,000 patients were referred to DPP through Medicare, in which about 1,000 of those referred actively enrolled into DPP. Referrals were isolated to doctors' offices, where screening was done to test for prediabetes of Medicare patients (Holliday et al., 2019). Overall, I surmised from the literature search that the results consistently revealed a need to improve the enrollment process into DPP (Mensa-Wilmot et al., 2018).

Using YouTube DPP to Bridge the Gap

Using YouTube as a mode for disseminating DPP content is still new to health educators and clinicians. As previously noted, not much study has been conducted to determine which content should be used, or how. With COVID-19 social distancing mandates in place, it is more difficult to screen and enroll participants into DPP.

However, theorists, like Madrigal and Mannan (2020) imply that YouTube can be leveraged to promote and advocate for better preventive healthcare. Madrigal and Mannan (2020) piloted a study utilizing health seminar videos hosted on YouTube.

Live health related seminars, approximately 60 minutes in length, were captured on video with permission from the audience over a period of three years. The audience was not audio recorded, nor videotaped during the seminar to protect privacy and adhere to the Healthcare Insurance Portability and Accountability Act (Madrigal & Mannan, 2020). The live video recordings of each seminar were cataloged, tagged, and indexed after each live recording, before being uploaded onto YouTube. The evaluation and overall performance of the videos were tracked with YouTube analytics for a period of three years after the initial uploading onto YouTube. Analytics included the number of total views, views per video, likes and dislikes, positive and negative comments, new subscribers, length of views, and the location of viewers. For instance, there were a total of 292,735 views and 50,764 hours of view time, spanning a global audience (Madrigal & Mannan, 2020).

Thus, the study provides evidence that YouTube extends local boundaries and provides more opportunities for a larger target market to access health information. Therefore, this study effectively approached the problem and highlighted research design methods and marketing strategies for me to incorporate into my study. Because Madrigal and Mannan's (2020) study was very explicit, I followed the design and methodology to formulate my own study instrument based on common resources, time constants, and analytics provide in the literature.

Common Knowledge in the Literature

Findings consistently indicated that challenges exist in screening and enrollment of patients into DPP. Holliday et al (2019) claimed that patients will have difficulties getting referred to DPP from physicians, if DPP on-site locations are difficult for patients to access or insurance coverage and compensations into such programs are not clearly defined. The issue is heightened during the COVID-19 pandemic (Clark et al., 2020; Fraticelli et al., 2020). Social distancing has made it even more difficult for referred patients to access on-site DPP (Lin et al., 2020). In addition, physicians are not able to see as many patients face-to-face to screen patient for enrollment into DPP (Parisien et al., 2020). Therefore, clinicians are experiencing difficulties screening, referring, and enrolling patients into DPP during the COVID-19 pandemic (Holliday et al, 2019). These factors have increased the demand for utilizing alternative means of reaching the patient population (Association American Diabetes, 2020). YouTube was suggested as an alternate way to educate and inform the patient population concerning diabetes preventive programs and self-management (Hasamnis & Patil, 2019). There is a consensus that online YouTube DPP can be used as a credible, effective tool for training, educating, and providing ways for behavioral change patterns within the audience (Kocyigit et al., 2020). It is accessible and a reliable method for getting health information to the public (Kocyigit et al., 2020). It crosses communication boundaries and health literacy concerns within vulnerable populations, according to Hasamnis & Patil (2019). It is understood that the information provided would need to be tailored to the needs of the local audience, and individuals from different backgrounds will require different types of health information to meet their health literacy needs (Kocyigit et al., 2020).

Controversies in the Literature

According to Rangarajan et al (2019), YouTube video channels are specifically engaging to younger adult viewers from 15 to 35 years of age. This may be a problem when trying to reach older viewers. There are also different health literacy levels to consider when recommending YouTube health information videos (Haslam et al., 2019). Another issue is that YouTube has a global audience that is not just local (Rangarajan et al., 2019). For instance, information published or broadcasted on YouTube is not guaranteed to solicit the intended target audience due to the global audience YouTube commands (Rangarajan et al., 2019; Vergeld et al., 2020). Soliciting a narrow target audience requires a focused marketing campaign strategy to ensure that the right individuals receive the message (Madrigal & Mannan, 2020). Another issue is the inconsistent health information provided on YouTube video channels (Kocyigit et al., 2020). Because there are different health literacy and competency levels to consider when suggesting YouTube health information videos, it is the responsibility of the healthcare provider to ensure that the patients have access to relevant content (Hasamnis & Patil, 2019). Mensa-Wilmot et al (2018) indicate that YouTube transcends health literacy issues. However, if the content is not presented accurately or in layman-terms then health literacy issues remain the same for the audience (Beck et al., 2017; Hasamnis & Patil, 2019). If the providers themselves are not familiar with the information on these YouTube channels it becomes difficult and less likely for providers to refer the videos

(Rutledge et al., 2018). Another issue is that there is no peer review or standard for the YouTube health information video content provided (Haslam et al., 2019). Even though it has been well-established that the information or content can be presented effectively, it is almost impossible to standardize the content on all YouTube channels (Haslam et al., 2019; Plohl & Musil, 2021). Another issue is that a majority of the health information is presented in the form of advertisements and not standardized by the CDC with evidence-based information (Haslam et al., 2019; Mondal & Mondal, 2020). Also, the YouTube recommendation system tends to use information based on contextual factors and agnostic factors as defined by Haslam et al. (2019) and Mensa-Wilmot et al. (2018). The research efforts of Madrigal and Mannan (2020) focused on video sharing utilizing YouTube. Madrigal and Mannan (2020) indicated that the poor use of YouTube as a leverage for generating awareness to increase health literacy must be addressed. The relevant results identified by Madrigal and Mannan (2020) work twofold for my study in that it defines the constructs of a well devised marketing strategy for health-related YouTube videos and suggests appropriate research designs.

Summation of the Gaps in the Literature

Because utilizing online YouTube DPP is a relatively new concept for the discipline, little is known about the accessibility of these programs to the target audience. There was also little evidence about how enrolling in online YouTube DPP influence behavior, attitudes, and self-efficacy in managing diabetes care (Devendorf et al., 2020; Kirkman et al., 2019). Mensa-Wilmot et al (2018) studied marketing strategies to assess dissemination barriers of DPP campaigns on multiple social media platforms. Results revealed deficiencies in reporting marketing performance measures, limited availability of online YouTube DPP, and referrals from clinicians to such programs (Mensa-Wilmot et al., 2018; Rutledge et al., 2018). Other issues included inconsistent marketing implementation, data collection, and reporting (Venkataramani et al., 2019; Zhou et al., 2020). And thus Mensa-Wilmot et al (2018) devised a marketing strategy to improve data collection for assessing performance outcomes. The implications by Mensa-Wilmot et al (2018), indicates that the ideal enrollment process would simultaneously have data collection strategies for assessing performance and key messages to engage participants and link them to risk testing, screening, clinician referrals, and continued engagement when enrolling in online YouTube DPP. Thus, the YouTube survey for this study also contained measures to assess some, if not all, of these assumptions.

According to Hasamnis et al (2019), YouTube is an amazing tool for teaching, learning, informing, and promoting health and well-being on a large scale. There is abundant information in these videos addressing health issues to help promote healthy lifestyles. However, Hasamnis et al (2019) states that the information is not compiled in a coordinated manner, making it difficult for the audience to systematically correlate the information together. Yet, YouTube reduces the need for face-to-face delivery of health information utilizing observational learning (Prybutok, 2020; Zepka et al., 2019). This was valuable information to consider when creating the survey for my study. The study attempted to stratify how social distancing and compliance has impacted the PI of enrolling in online YouTube DPP. The information added to the body of knowledge that was lacking concerning attitudes towards enrollment into YouTube DPP.

Rational for Selecting the Key Variables

Statistics generated by Pew Research Center (2019) indicated that more than 70% of the U.S. population watched YouTube videos in 2019, and research by Haslam et al. (2019) shows YouTube to be effective in presenting health information. Haslam et al (2019) explored the extent of social media popularity concerning health related information. Results indicated that medical information disseminated to audiences through YouTube provided ample training, access, and performance analytics (Gimenez-Perez et al., 2020; ReFaey et al., 2018). It also indicated the need for future requirements for sustainable structured learning (Madrigal & Mannan, 2020). A systematic integrative review was conducted using frameworks based on Whittemore and Knafl (Haslam et al., 2019). The methodology supported a holistic, unbiased integration of different research designs to address the validity of YouTube health information videos (Haslam et al., 2019). The study focused on three dynamics for determining the validity and effectiveness of utilizing YouTube health information videos; (1) the validity of the health information content provided in YouTube videos, (2) the effectiveness as a decision-making tool for the treatment, prevention, and diagnosis of disease, and (3) the reliability of accessing health related information on YouTube channels (Haslam et al., 2019). Sixty-seven studies met the inclusion criteria determined by CASP standards as a guide from an initial 695 studies identified in scientific databases. Twenty studies were of high validity, proving that the YouTube platform can be used as a credible method for disseminating health information. Nine studies demonstrated the effectiveness of utilizing YouTube health information videos for imparting self-efficacy, knowledge, and behavioral and attitude change when compared to written documentation on other social media platforms. Finally, 10 studies were selected from the top search results list to determine the accessibility of credible health information to the public on YouTube. Findings indicated that three factors impacted the availability of YouTube health information videos disseminated to the public; (1) the video content must be between 3 to 5 minutes in length, fast-paced, emotionally invoking, relatable, and from a credible source, (2) video diagnostic factors would indicate a high number of views in a short period of time after being recently uploaded, and (3) the YouTube health information videos must be ranked high on YouTube recommendations list, where 80% of YouTube video views are derived. Thus, the information in this study was not only relevant for devising the appropriate methodology for data collection and analysis of online YouTube DPP videos, but the reasoning for selecting it as a variable for the study.

The significance of using YouTube videos during COVID for effective pre-diabetes self-monitoring as a part of the patient care continuum was outlined by Mondal and Mondal (2020). An observational study based on clinical glucose self-monitoring practices collected from the National Center for Biotechnology Information Search database, prompted a two staged screening and analysis focused on self-monitoring of blood glucose on YouTube videos. The data collected emphasized video content, i.e., strip and lance handling, site and hand hygiene, and proper measurement and maintenance procedures. About 40% of the YouTube videos content analyzed contained accurate and effective information on strip and lance handling. Information on site and hygiene were about 70% accurate and effective. about 60% of the information on proper measurement and maintenance procedures presented on YouTube videos were effective and accurate. Results were consistent in that YouTube was effective in providing effective and accurate pre-diabetes self-monitoring information to patients during the COVID pandemic (Al-Hasan et al., 2020; Prybutok, 2020; Rangarajan et al., 2019). However, care must be taken when selecting the most appropriate videos for patients, due to the different levels of completeness (Kocyigit et al., 2020). Therefore, this study provided specific quantitative data to identify the structural content of effective pre-diabetes self-monitoring YouTube videos during the COVID pandemic to model in my research.

Social Distancing, Compliance, and Perceived Importance Assumptions

Social Distancing

There are dangers of misinforming the patient population with unclear directions and procedures during the COVID pandemic (Nye, 2020). This illustration would have similar implications to health videos missing key messages and interaction to risk testing, referrals, and enrollment into DDP (Kocyigit et al., 2020). The article supported my study by identifying the missing information which reduces the referral and enrollment rates into DDP. Due to social distancing mandates, individuals have less contact with clinicians and are unable to receive the care and counseling that they would normally receive. Because of social distancing, some patients have been isolated from caregivers, clinicians, and the healthcare community in which they rely on to receive valued health related instruction and care. Nye (2020) addressed the dangers of misinformation to patients during the COVID pandemic due to social distancing. Therefore, online education has now become valuable in bridging some of these communication gaps and severed connections caused by social distancing mandates. There is limited information available causally relating social distancing to DPP awareness and prevention on YouTube. Most of the general information is related to social distancing and how social distancing has limited the amount of face-to-face contact and exposure patients have accessing DPP sites. This study focused on social distancing as it relates to DPP to add to the body of knowledge that is lacking in practice.

Compliance

Compliance to social distancing guidelines is based on one's personal value system and desire to not contract the Coronavirus (Chan et al., 2020). Because individuals do not want to become infected with the Coronavirus, they would then adhere to the social distancing norms and guidelines (Clark et al., 2020). This means that individuals would wear their face mask, wash their hands, wipe down surfaces, maintain 6 feet distances from other individuals in public places, avoid crowds, and public areas by staying home (Clark et al., 2020). A greater public/global concern for health and wellbeing of all citizens due to the pandemic, encouraged individuals to be more compliant (Zajenkowski et al., 2020). As a result, however, individuals would be isolated from others in the community that they would normally have contact with. Therefore, higher levels of compliance increased the isolation that individuals experienced from withdrawing from the community and thereby increased the need to seek out different ways to communicate with others through the internet (Kocyigit et al., 2020). This meant that individuals had to connect and communicate in different ways other than face-to-face contact, increasing the use of the internet to bridge the gap in connections (Chiou & Tucker, 2020). In short, people were now looking for different ways to spend their time through entertainment and interactive learning through YouTube (Chiou & Tucker, 2020; Haslam et al., 2019). YouTube has become a vital tool in connecting individuals to health information that they would have normally received through face-to-face interaction.

Perceived Importance

The goal of this study was to identify if there was a difference between compliance groups based on the PI of getting diabetes education and self-management information from enrolling in online DPP videos on YouTube. De Silva et al (2020) outlined ways in which diabetes could be screened utilizing digital platforms during COVID. The implications support using YouTube as a platform to find new ways of predicting behaviors and attitudes of high-risk diabetic populations. Because most of the public is isolated from clinicians and healthcare workers during the pandemic, enrolling in YouTube DPP, many be perceived as more important than before. However, it has not been identified if such information is important to the population, or if the public finds value in enrolling in YouTube DPP. The assumption is that individuals that are very health conscious and more opened minded towards enrolling in YouTube DPP to manage their health (De Silva et al., 2020). This would imply a greater acceptance of enrolling in YouTube DPP due to social distancing and an individual's personal compliance level. For example, an individual's PI of accessing relevant YouTube DPP videos online may be heightened if that individual is highly compliant to social distancing mandates. The more value people place on enrolling in YouTube DPP, the more exposure and viewing engagement people will experience (De Silva et al., 2020). This will also prompt the development of more evidence-based type 2 diabetes prevention programming than currently available. More evidence is needed to support the assumption, so this study sought to understand whether enrolling in YouTube DPP were perceived as valuable to the public. Haslam et al (2019) highlighted the validity and reliability of the health information disseminated on YouTube. The study conducted by Haslam et al (2019) demonstrated that it was possible to collaborate with teams and promote effective decision-making utilizing YouTube videos. However, that does not substantiate whether the health information is valued enough by the public for viewing, nor whether the public would enroll in YouTube DPP if the programs were a part of the YouTube recommendation system. Haslam et al (2019) supported the need for incorporating these assumptions and questions into an evidence-based study survey using SCT as a theoretical framework, when investigating the PI of enrolling in YouTube DPP for better lifestyle decision making. Therefore, these assumptions and questions were incorporated into this survey to assess the attitudes and perceptions of high-risk diabetic populations using SCT as a framework.

Summary and Conclusions

Major Themes and Assumptions

Because diabetes has become so prevalent, it is crucial for the CDC to stop its proliferation. DPPs serve as a national prevention tool for increasing the awareness and self-management for diabetes. However, due to poor screening and enrollment practices, less than 2% of the target population uses it (Barry et al., 2017; Holliday et al., 2019).

Social distancing mandates, due to the COVID-19 pandemic, make the screening and enrollment practice matters worse (Calo et al., 2020). Evidence shows that YouTube is a responsive tool for all audiences on a global scale (Gimenez-Perez et al., 2020). Information can be effectively taught from an observational standpoint, which works well with the SCT framework for this study (Chen et al., 2017). It is a common assumption that individuals who are compliant to social distancing mandates are the most health conscious (Chan et al., 2020; Clark et al., 2020). These individuals may be open-minded in looking for new ways to connect to the health community during the COVID-19 pandemic. These individuals may also have a high sense of self-efficacy, which allows them to pursue different strategies to connect to the health community, like enrolling in YouTube DPP (Li et al., 2020; Xie et al., 2020). This type of engagement was significant in the observational learning identified in the SCT framework for this study, in which I sought to identify the PI or value of enrolling in YouTube by the audience (Bandura, 1986; (Mohebbi et al., 2019; Mondal & Mondal, 2020). Results may help determine better enrollment practices for YouTube DPP to help monitor diabetes for better management, ensuring prevention through essential behavioral change.

The Consensus of Knowledge

Because of the COVID-19 pandemic, reaching the population and educating them about type 2 diabetes self-management, in terms of prediabetes screening and enrollment into DPP, is of utmost importance (B, 2020). However, YouTube DPP video information is remarkably diverse even if it can be used to systematically address the health literacy needs of the audience (Haslam et al., 2019; Zhou et al., 2020). In other words, the information needs to be standardized.

Common Contradictions About Basic Assumptions

Even though YouTube DPP is considered a great learning tool, it is controversial if the audience finds enrollment into YouTube DPP as valuable during the COVID-19 pandemic. Chen et al. (2017) and Mohebbi et al. (2019) indicated that little evidence-based information exists to confirm the level of self-efficacy that the online community has about enrolling in YouTube DPP. There is no consensus about the relevant information that is necessary to meet the diverse health literacy needs concerning type 2 diabetes within the online population (Holliday, 2019). So, it is not clear how practitioners could best organize YouTube DPP in the YouTube recommendation system for the target audience to successfully navigate and enroll in YouTube DPP (Haslam et al., 2019). However, Mondal & Mondal (2020) asserts that if people start seeing YouTube DPP as part of their YouTube recommendation, that alone may increase their PI of enrolling in YouTube DPP. Therefore, this study investigated whether there was a PI of enrolling in YouTube DPP due to SDC levels during the COVID-19 pandemic. This helped indicate if individuals with higher self-efficacy would engaged more frequently in YouTube DPP.

Gaps Extending the Knowledge of the Discipline

Whiles there are gaps in the literature extending from poor utilization of the YouTube recommendations system, there is also little evidence identifying whether the online audience have enough self-efficacy and health consciousness based on their SDC levels to value enrolling in YouTube DPP during the COVID-19 pandemic (Chan et al., 2020; Xie et al., 2020; Zepka et al., 2019). So, this study used the SCT framework to focus on understanding the PI of enrolling in YouTube health related videos by the online general audience as it pertains to their SDC levels. Evidence may help practitioners determine how the online audience may respond to YouTube DPP during the pandemic based on attitudes and beliefs from using the SCT framework. Results may help clinicians and diabetes health specialists employ better observational learning techniques to advocate and increase self-efficacy to connect to the general population through YouTube DPP. Then, the U.S. adult population can use YouTube DPP for better diabetes self-management to promote diabetic free lifestyles.

Social Change Implications

Prior studies employed the YouTube recommendation methods found in the YouTube analytics system to analyze the effectiveness of YouTube health content utilization (Madrigal & Mannan, 2020; Rangarajan et al., 2019). In other words, most literature used YouTube analytics to determine the value and viability that the audience placed in observing YouTube healthcare information content. However, there is not enough evidence to establish purposeful social change implication in terms of the perceive benefit of positive attitudes towards enrolling in YouTube DPP by the online population (Mohebbi et al., 2019). Therefore, this study attempted to fill the gap and bring about positive social change implications by identifying perceived attitudes towards enrolling in YouTube DPP during the COVID-19 pandemic based on SDC levels. The results may help bring about social change by determining which methodologies to use for constructing new YouTube DPP content. Clinicians may be able to understand the level of self-efficacy and value that the audience place on enrolling in YouTube DPP. The next step would be to determine whether the recommendation services found on YouTube are effective in increasing the level of PI of enrolling in YouTube DPP. However, the focus of this study was on observing the PI through SDC. The assumption that individuals have a higher sense of self-efficacy and health awareness, which makes them open minded to enrolling in YouTube DPP, was observed through the survey.

Connection to Methodology

This cross-sectional quantitative study, in the form of a Likert scale 30 close-ended question survey, hosted on SurveyMonkey, a reliable platform for online accessibility and participation during the social distancing climate of the pandemic, sought to identify SDC levels and the PI of enrolling in YouTube DPP in the general online population (SurveyMonkey, n.d.). The results would add to the body of knowledge by predicting behaviors and attitudes towards enrolling in YouTube DPP. Since prediabetes impacts 1 in 3 U.S. adults in the general population, the general population would serve as a participant pool for the study. IBM SPSS Statistics 28, data software package was used for correlating results (IBM, n.d.). When collecting data, no ethical concerns, or considerations were violated concerning the enrolling in YouTube health related content because of the opened access of the YouTube platform. In-depth information about the research question, the target population, the form of survey questionnaire used, the survey marketing strategy, and the survey hosting instrument, was expanded on in Chapter 3.

Chapter 3: Research Method

Introduction

The social cognitive framework was applied to my nonexperimental, retrospective, cross-sectional study approach to help assess the PI of enrolling in online health related YouTube content, particularly diabetes prevention videos, relative to participant SDC levels. Since the onset of COVID-19, it has become difficult for health providers to connect with patients as before (Yin et al., 2020). The patient-doctor relationship through conventional means during office visits has been disrupted by social distancing mandates (Calo et al., 2020; Holliday, 2019). If a demand for enrolling in online YouTube DPP exist, it could reestablish bonds within the patient care continuum and empower enrollment into DPP through the YouTube platform (Zhou et al., 2020). Ideally, the online U.S. adult population may learn to manage and maintain healthier diabetic free lifestyles through online YouTube DPP at their own rates and comfort zones (Zhou et al., 2020).

The rest of this chapter presents information on the research design and rationale, covering design strengths and limitations in depth. In addition, I expand on the key variables, variable measurements, and the null and alternative hypothesis in response to the research question. I also discuss the methodology, target population, sampling procedures, data collection process, instrumentation and operationalization, and the threats to the internal and external validity of the instrumentations used in the study.

Research Design and Rationale

As mentioned earlier, I approached the research design as a quantitative nonexperimental, retrospective, cross-sectional, self-reporting questionnaire, and used a Likert five-point scale, hosted on SurveyMonkey, where SDC represented the independent variable and the PI of enrolling in online YouTube DPP represented the dependent variable. Since the data from my research question captured point-in-time reflections of the participant's PI of enrolling in online YouTube DDP corresponding to their SDC, my research design worked appropriately for collecting data specifically for that task, according to Al-Hasan et al. (2020). The research question asked participants to reflect or take a retrospective composite on their observed attitudes and behavioral patterns in response to the COVID19 social distancing mandates and their PI of enrolling in online YouTube DPP during that same point-in-time, which was a cross-sectional design. According to Vergeld et al. (2020), Lin et al. (2020), Al-Hasan et al. (2020), and Kocyigit et al. (2020), the best way to collect accurate inexpensive data with minimal interviewer bias was through a self-reported questionnaire.

The project was allocated $2,000 and data collection commenced for a few weeks until 300 volunteers were acquired for the study. Participants were given an online anonymous survey with 36 close-ended questions. Due to time constraints and limited resources, the retrospective, cross-sectional, self-reporting questionnaire was the most inexpensive and easiest approach to implement for my study purposes when compared to other designs and research methods (Kocyigit et al., 2020).

Since the SCT was commonly used in health education and promotion for validating evidence-based research, my design rationale could be adapted to fit other social science studies, settings, populations, and real-world situations. Vergeld et al. (2020), Lin et al. (2020), Al-Hasan et al. (2020), Kocyigit et al. (2020), and many other researchers used the quantitative, nonexperimental, cross-sectional, self-reporting questionnaire and SCT framework to further advance the body of knowledge in the social science community. Similar design and framework would advance my study in the discipline as well. In short, my hope was for this study to be as generalized as possible so it would be recognized and incorporated into other studies, even though it stems from limited time and funding constraints.

Methodology

Population

The target population represents the U.S. adult online community, e.g., excluding individuals that were younger than 18, and pregnant women. Since almost one in three U.S. adults have prediabetes without knowing (Centers for Disease Control and Prevention, 2020) and about 80% of the U.S. adult population rely on YouTube content, it was feasible to select the U.S. adult online community as viable participants for the study, when considering limited constraints on funding and time (Omnicore Group, 2021; Pew Research Center, 2021).

Sampling and Sampling Procedures

I used a probabilistic sampling method and randomized selection since the online U.S. adult community were selected as the target population out of convenience, availability, and the constraints mentioned earlier. According to the Pew Research Center (2021), young adults and middle-aged Americans accounted for most of the online population (Zhou et al., 2020). Consequently, the process for selecting my online participant population relied heavily on choosing computer literate participants, which excluded some vulnerable populations and the elderly (Rangarajan et al., 2019). Facebook, LinkedIn, Instagram, and Twitter were the social media used to draw the sample pool out of convenience due to my limited budget and time constraints (Zhou et al., 2020). Therefore, the online U.S. adult target population were not randomly selected when the general population was considered.

Unfortunately, the probabilistic sampling method made it difficult for me to get an accurate representation of the prediabetic and diabetic online study participant pool when compared to the general prediabetic and diabetic U.S. adult population, which includes older adults, young adults, and middle-aged Americans, on or offline. In addition, individuals under the age of 18 and pregnant women were excluded from the study because they do not represent the general U.S. adult population with prediabetes or diabetes in accordance with HealthyPeople2030 criteria (Centers for Disease Control and Prevention, n.d.). Therefore, I focused on determining SDC levels with attitudes towards enrolling in online YouTube DPP from the online participant population without associating those diagnosed with prediabetes and diabetes, since I could not accurately account for the prediabetic or diabetic U.S. adult population in my study (Mellinger & Hanson, 2020). In summation, the representation of prediabetic and diabetic online participants in my study may be biased, even if participants were identified as prediabetic or diabetic, due to the nature of the non-probabilistic online sampling method that was used.

Power Analysis and Sample Size

Based on the IBM SPSS G*power of analysis software version 28 (IBM, n.d.), a sample size of at least 200 was required for the five SDC level groups as the number of predictors using a one-way ANOVA associated with an approximate target online U.S. adult population of over 100,000. That includes an alpha level of 0.05, with a standard power level of 0.80, and an effect size of 0.25 (Clark et al., 2020; Kaufman, 2019; Li et al., 2021). To enhance the effect, I increased the sample size from 200 to 300. Doing so negated some inconsistencies due to missing data. Please note that the sample size calculation substantiating my study was initially based on prior studies with target populations over a 100,000 and therefore validated my rational for using the G* power analysis IBM SPSS software version 28 (Li et al., 2021; IBM, n.d.). The post hoc was used to verify the null hypothesis, while Cronbach's alpha was used to substantiate the internal reliability of the study instrument (Li et al., 2021).

Procedures for Recruitment, Participation, and Data Collection

Participants were recruited based on Mensa-Wilmot et al. (2018) marketing techniques, like flyer campaigns, word of mouth marketing, and using social media campaign tags on LinkedIn, Facebook, Instagram, Twitter, and SurveyMonkey. Participants anonymously accessed the online survey link connecting them to the questionnaire hosted on SurveyMonkey, where participants would read the instructions, confirm their informed consent to participate, and answer the close-ended questions hosted in the online survey. Age, sex, location (United States or other), education, and health conditions were the only demographic information requested (see Table 2). Participants could have ended participation at any time during the survey by closing the survey browser or leaving the SurveyMonkey survey website. Participants were given the opportunity to view study results by checking into the same survey website after the study was completed.

Table 2

Participant Demographic Questions

Questions	Demographics	Response	Measure	Code	Criterion
1	Age	Numeric age	Scalar	1,999	18yrs and older
2	Sex	Male or female	Nominal	(1) Male (2) Female	None
3	Location	United States or other	Nominal	(1) United States (2) other	U.S. participants only
4	Education level	□ Elementary school □ Grade school/Intermediate □ High school □ Junior College □ Four years College □ Professional/Trade school □ None	Nominal	(1) Elementary school (2) Grade school/Intermediate (3) High school (4) Junior College (5) Four years College (6) Professional/Trade school (7) None	None
5	Health condition	□ Heart disease □ Prediabetes or diabetes □ Cancer □ Lung disease □ High blood pressure □ Obesity □ Pregnant or lactating	Nominal	(1) Heart disease (2) Prediabetes or diabetes (3) Cancer (4) Lung disease (5) High blood pressure (6) Obesity (7) Pregnant or lactating	Excluding pregnant women

	□ Other	(8) Other
	□ None	(9) None

Instrumentation and Operationalization of Constructs

Since no specific survey instrument previously developed could fulfill my research goals and answer my research question, source instruments were used to devise an appropriate tool. According to Mara and Peugh (2020), modifying survey instruments to fit research objectives could lower the validity of the study. However, using prior instruments previously validated with analytical statistics, like the one-way ANOVA analysis, were feasible for helping me develop a new survey instrument when short on time and resources (Mara & Peugh, 2020). Therefore, to fulfill my study goals, it was appropriate to analyze credible survey instruments and then establish the internal validity of my newly developed instrument scale with factor analysis, as mentioned by Mara and Peugh (2020).

Survey Instrument

According to the National Business Research Institute (2021), it was important to use survey questions that measured the variables and answered the research question with credible survey instruments. I used three commonly used survey instruments that were readily available to the public on the NIH open-source access site as BSSR research tools (see Table 3). Mellinger and Hanson (2020) indicated that these survey tools would answer my research question if I implemented the same questionnaire strategies for sequestering participant responses for my study purposes. Asking similar questions in groups ensured reliability and consistency in participant response, helping to establish internal consistency, which was then analyzed for validity using Cronbach's alpha (Mara & Peugh, 2020).

Table 3

BSSR Published Instrument Sources

Instrument	Developer(s)	Published date	Appropriateness	Open access link
The Global survey on COVID-19 beliefs, behaviors, and norms Survey	Collis, A., Garimella, K., Moehring, A., Rahimian, M.A., Babalola, S., et al. (2020) as a technical report for MIT Sloan School of Management	November 30th, 2020	Reflects the beliefs and attitudes of US population concerning SDC behaviors and utilization of YouTube health related videos for common COVID-19 survey tools	The survey instrument can be accessed in the PDF file of the document where it states the following: (Data Access Updated aggregate data can be found ***here***, and researchers can request access to respondent-level responses (microdata) by requesting access ***here***.) https://www.nlm.nih.gov/dr2/COVID-19_BSSR_Research_Tools.pdf
The JHU COVID-19 Community Response Survey	Mehta, S. at Johns Hopkins Bloomberg School of Public Health	April 25th, 2020	Reflects the US population demographics and characteristics for common COVID-19 survey tools	https://www.nlm.nih.gov/dr2/JHU_COVID-19_Community_Response_Survey_v1.3.pdf (ID: 22096)
The United States National Library of Medicine, COVID-19 BSSR Research Tool	Operated by the NLM within the National Institutes of Health (NIH), located in Bethesda, Maryland	n.d.	Comprehensive assessment of different theoretical frameworks used in common health science survey tools	https://www.nlm.nih.gov/dr2/COVID-19_BSSR_Research_Tools.pdf

The internal validity or consistency of the five-point Likert scale in my study was confirmed by analyzing the Cronbach's alpha coefficients. According to Leppink and Pérez-Fuster (2017), Cronbach's alpha is well established for assessing the validity of questionnaire scales that group questions with the same types of activities and concepts as defined in my study (Vet et al., 2017). If there were differences in the concepts or activities administered in the line of questioning, the Cronbach's alpha would be a poor indicator of validation for the scale being used (Mellinger & Hanson, 2020; Vet et al., 2017). For example, SDC measured the frequencies of performing similar actions and PI measured attitudes or perceptions towards performing different tasks. Since SDC and PI activities and concepts differ, questions about SDC and PI had separate 5-point Likert scales and assessed independently using Cronbach's alpha (see Table 4 and Table 5).

Table 4

Social Distance Compliance Five-Point Likert Scale (McLeod, 2019)

Frequency rank/value scale					
Responses	Never	Rarely	Sometimes	Often	Always
Point code	1	2	3	4	5
Scale	1	2	3	4	5

Note. Scale was measured on a 5-point Likert scale from one to five points and scored lowest value to highest value for each response. Total lowest score value = 1; Total highest score value = 5.

Table 5

Perceived Importance (PI) Five-Point Likert Scale (McLeod, 2019)

Importance rank/value scale					
Responses	Not important	Little important	Important	Very important	Absolutely important
Point code	1	2	3	4	5
Scale	1	2	3	4	5

Note. Scale was measured on a 5-point Likert scale from one to five points and scored lowest value to highest value for each response. Total lowest score value = 1; Total highest score value = 5.

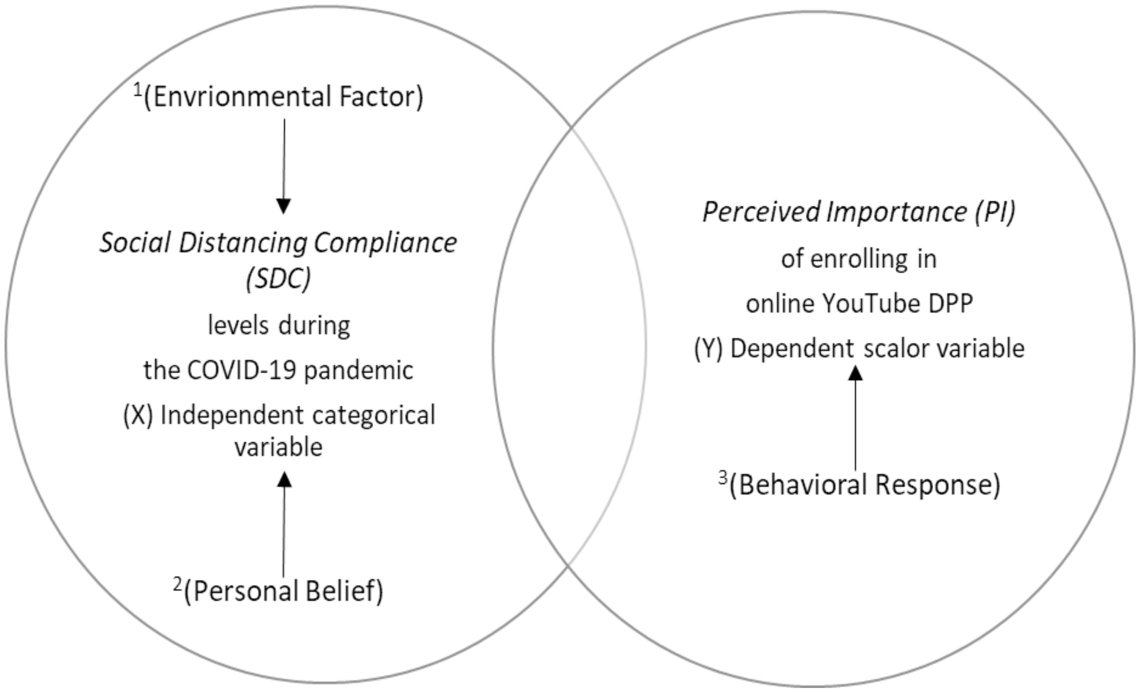
Similar questions were asked pertaining to the SDC levels and received importance of using YouTube health related videos referenced in the Global survey on COVID-19 beliefs, behaviors, and norms survey instrument. Another set of questions reflected population demographics and characteristics outlined in the JHU COVID-19 Community Response Survey Instrument. Finally, the United States National Library of Medicine COVID-19 BSSR research tool served as the groundwork for the social cognitive theoretical framework in the study.

A total of 36 questions, which reiterated my research goals and criteria, were compiled from the three survey instruments to host on SurveyMonkey. Hosting the survey instruments on SurveyMonkey was very cost effective for my low-cost budget, and the survey tool seamlessly integrated the research question based on the SCT framework into an online questionnaire for easy implementation. So, SurveyMonkey was quite effective in helping me host the survey instrument for the general online population.

This SDC and PI of YouTube DPP survey tool constructed from the SCT as the framework, allowed me to capture the attitudes and opinions of participants utilizing close-ended questions (see Figure 4). The research question was devised to capture the ideals and understandings of the general online U.S. adult community, as it pertained to SDC and the utilization of YouTube for better diabetes self-management.

Figure 4

Social Cognitive Framework for SDC and PI



Note. The SCT has been adapted for the framework of this study. [1]Environmental factor reflects the observational learning constructs regarding social distancing practices from the participant's perspective based on COVID-19 social distancing norms, or mandates. [2]Personal belief reflects the participant's level of self-efficacy regarding compliance, or SDC levels. [3]Behavioral response reflects the participant's attitude towards enrolling in online YouTube DPP.

Administration of the Instrument

Administration was through various online social media points, such as Facebook, through the SurveyMonkey platform. Participants accessed the questionnaire through a link that was hosted on SurveyMonkey that evaluated the attitudes and opinions of the general online population. Initially, participants responded to an advertisement linking them to the survey questionnaire, in which they responded to 36 close-ended questions through the SurveyMonkey online portal. Participants then read the instructions explaining the criteria for participation and how to answer each question. Qualified participants then responded by ranking each question based on a one to five scale seen in Table 4 and Table 5 previously. There was no special permission needed for a participant to respond to the questionnaire. The survey took no more than 10 minutes for participants to complete, and participants only needed access to the internet from their cell phone, wearable device, tablet, or PC.

Operationalization for Key Variables

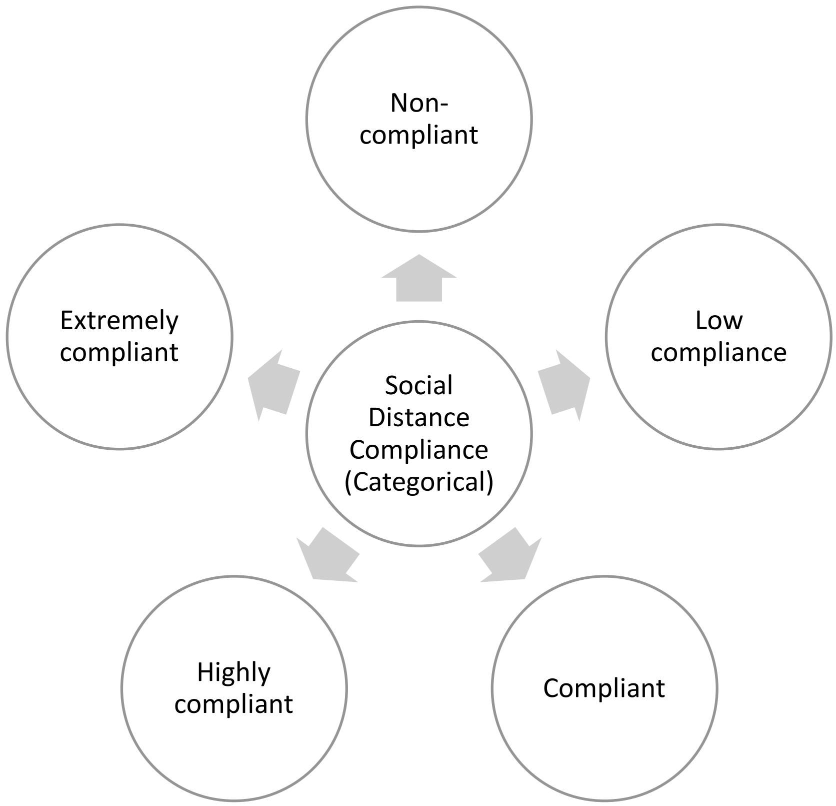
My study had two variables described in Figure 4 above, SDC and the PI of enrolling in online YouTube DPP. Both variables were measured based on a Likert scale of one to five and statistically analyzed with IBM SPSS version 28 software. The raw data, which was collected on SurveyMonkey, was downloaded, and coded for further differential analysis with descriptive statistics and a general linear one-way analysis of variance (ANOVA).

Independent (X) Variable

Data collected from responses participants made to a series of questions on SDC, the independent variable, were categorized using mean frequencies into five SDC categories.

Figure 5

Independent (X) Variable Categories



The mean frequencies of the participant's scores helped with placement into noncompliant, low compliance, compliant, highly compliant, and extremely compliant categories (see Figure 5). A group of five SDC questions, were each measured on a scale of one to five, to identify the participant's level of compliance. The mean scores were calculated from summing the cumulative raw scores of the five questions, which ranged from five to 25. This helped me denote the placement of each participant into the respective groups.

Question number six asked how often participants wash their hands, another question asked whether participants cover his or her mouth when sneezing, another question asked whether participants maintained a six feet distance in public places, and another question asked if participants stayed home from work when sick (see Table 6). Based on a one to five scale, participants indicated their level of compliance to each question (see Table 4). Both SDC constructs (government mandates and personal measure seen in Table 6 and 7) scores were compiled based on the one to five scale for each question. Ten was the lowest score and 50 was the highest score that participants could receive based on all 10 government mandates and personal measure questions concerning SDC. Therefore, scores 10 through 50 helped me determine the five different groups for SDC with the use of SPSS version 28 software.

Table 6

Social Distance Compliance (SCT Constructs: Government Mandates)

To stop the spread of COVID-19 in the community and to others, do you do the following:						
Question number	Government mandates questions	5-point Likert Scale*				
		Never	Rarely	Sometimes	Often	Always
6.	Wash your hands frequently?	1	2	3	4	5
7.	Stay home when feeling sick?	1	2	3	4	5
8.	Stay indoors to stop the spread?	1	2	3	4	5
9.	Keep 6-feet distances in public?	1	2	3	4	5
10.	*Wear a face mask in public?	1	2	3	4	5

Notes. * Score range and ranking = 1 the lowest to 5 the highest. Cumulative government mandates score = 5 the lowest to 25 the highest.

Table 7

Social Distance Compliance (Social Cognitive Theory Constructs: Personal Measures)

To stop the spread of COVID-19 and keep oneself and/or your family safe/well, do you do the following:

Question number	Personal measures questions	5-point Likert Scale*				
		Never	Rarely	Sometimes	Often	Always
11.	Watch the news?	1	2	3	4	5
12.	Wash/wipe off groceries?	1	2	3	4	5
13.	Cover mouth when sneezing or coughing?	1	2	3	4	5
14.	Cook your own meals?	1	2	3	4	5
15.	*Shower after going outside?	1	2	3	4	5

Notes. * Score range and ranking = 1 the lowest to 5 the highest. Cumulative Personal measures score = 5 the lowest to 25 the highest.

To clarify, 10 to 18 represented the range for the "non-compliance" category (see Table 8). The second group, "low compliance," ranged from 19 to 26. The next group, "compliant scores," ranged from 27 to 34. The next group was "highly compliant," and ranged from 35 to 42. And the last group, "extremely compliant," ranged from 43 to 50 (see Table 8). Thus, participants were placed into the five categorical groups depending on the score ranges mentioned above.

Table 8

SDC Categorical Score Ranges

Categories	Noncompliant	Low compliance	Compliant	Highly compliant	Always compliant
Score ranges	10 to 18	19 to 26	27 to 34	35 to 42	43 to 50

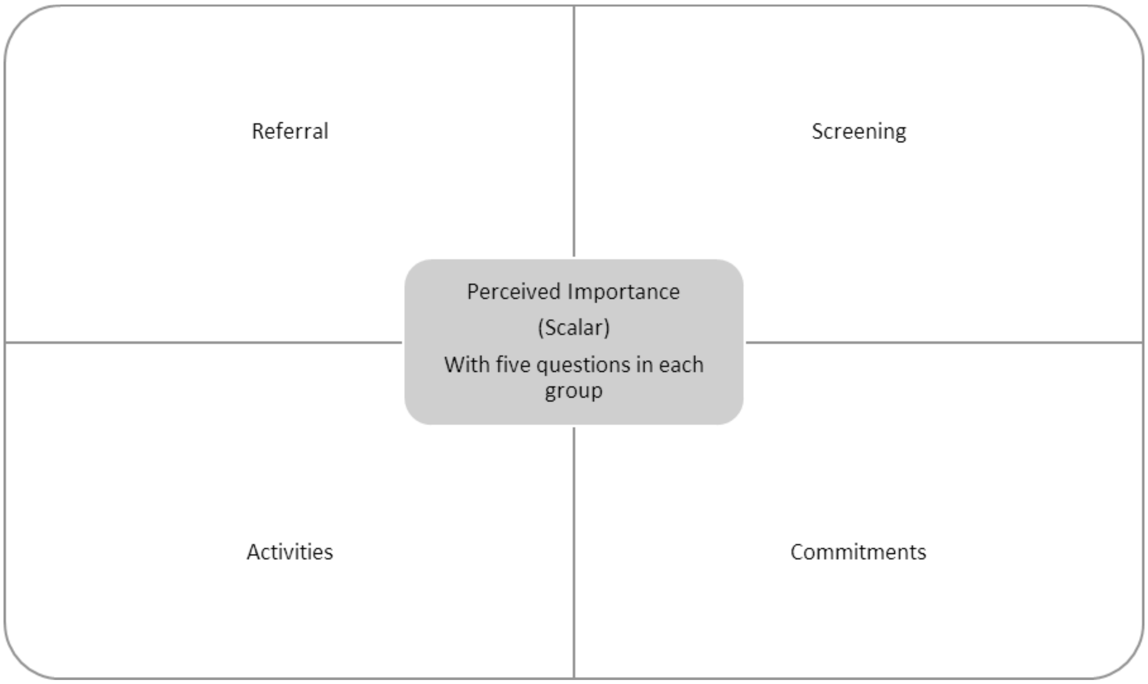
Note. Cumulative score range = 10 the lowest to 50 the highest

Dependent (Y) Variable

The PI dependent scalar, or continuous, variable was measured from 20 cumulative responses, based on a one to five, Likert scale, scored from 20 to 100. But first, data was collected on the dependent variable, the PI of enrolling in online YouTube DPP from anonymous participants responses hosted on SurveyMonkey derived from the SCT construct (see Figure 6). PI questions were arranged into four social cognitive constructs concerning well-established referral, decisions, screening, and enrollment practices and strategies applied by practitioners to assess the PI scores of participants, as in Figure 6 (Ackermann et al., 2019; Barry et al., 2017; Brown, 2019; Chen et al., 2017; Holliday, 2019; Mensa-Kwao et al., 2019; Mensa-Wilmot et al., 2020; Venkataramani et al., 2019).

Figure 6

Dependent (Y) Scalar Variable Construct for the SCT Framework



Note. Groups represent the SCT construct for the dependent variable which were compiled into a cumulative score for each participant. A total of 20 questions (i.e., five questions in each construct group) for each participant was compiled for scores ranging from 20 (the lowest score) to 100 (the highest score).

As seen in Table 8, the first five SCT construct questions asked participants how important commonly used online referral practices were at influencing them to enroll in YouTube DPP (Barry et al., 2017). Then, participants were asked five more SCT construct questions to uncover the importance of common online YouTube DPP activities when making their decision to enroll and prevent diabetes (Chen et al., 2017; Holliday, 2019). The next five SCT construct questions focused on the participant's PI of the online YouTube DPP screening process for enrollment into the program (Mensa-Kwao et al., 2019; Mensa-Wilmot et al., 2020). The final five SCT construct questions focused on the participant's attitude towards personal commitment and responsibilities needed after enrollment into YouTube DPP, as seen in Table 9 (Ackermann et al., 2019).

Table 9

Perceived Importance (Enrollment Process Questions)

Question #	Referral	Question #	DPP activities and content	Question #	Screening	Question #	DPP commitments
16	When an official online social media sends you a link	21	Group events	26	Knowing diabetes and prediabetes prevention, treatment, and medication cost	31	Spending 20 to 40 minutes online sessions
17	When your primary doctor sends you a link	22	Exercise regiments	27	Knowing your risk for diabetes and prediabetes	32	Using a smartphone or other devises to participate
18	When an acquaintance sends you a link	23	Personal control skills	28	Knowing your blood sugar level	33	Subscribing to online YouTube DPP channels
19	When family tells you about a link	24	Motivational coaching	29	Knowing about your coverage	34	Keeping up to date with online YouTube DPP
20	An acquaintance tells you about it	25	Diabetes recipes	30	Knowing about blood sugar medicine advantages and disadvantag es	35	Buying what you saw on YouTube DPP

The response to each question arranged within the four SCT construct groups denoted the participant's PI on a scale of 1 to 5. Each question (20 in all) ranged from one to five on the Likert scale and was score from 5 to 25 in the respective group (see Figure 10). For example, 1 on the 5-point scale was presented to participants as not important, 2 was presented as a little important, three was presented as important, four was identified as very important, and 5 on the scale was denoted as absolutely important, as seen previously in Table 4 (McLeod, 2019; Machackova & Smahel, 2018). Seen in Table 10, the participant's PI score, ranged from 20 to 100, was compiled from the cumulative score (averaging together the mean scores of every PI question arranged within the four groups).

Table 10

PI Enrollment Question Score Ranges

SCT construct groups	Referrals	DPP activities	Screening	DPP commitments	*Total
Score ranges	5 to 25	5 to 25	5 to 25	5 to 25	20-100

Note. *Cumulative score range = 20 the lowest to 100 the highest.

The composite score for the PI variable ranged from 20, the lowest score, to the highest score, 100, depending on participant response (see Table 10). Statistical assessment with ANOVA identified the mean differences needed to determine significance and answer the research question, i.e., if there is significance between SDC and PI of enrolling in online YouTube DPP. Again, scores ranged from 20, the lowest of importance, and 100, the highest of importance, for enrolling in online YouTube DPP videos within the SDC categories for PI. Therefore, some indication will be made to the degree of importance for enrollment practices within each SDC category based on statistical results derived from the ANOVA.

Data Analysis Plan

SurveyMonkey, a commonly used online survey platform, served as the survey instrument for hosting my study tool "COVID-19 Blood Sugar Wellness Survey". Since 1999, the organization has developed into a diversified survey hosting platform used for hosting various types of questionnaire and survey instrument formats including open-ended, close-ended, multiple choice, fill-in the blank, matching, grouping, and sequential questionnaires. SurveyMonkey was used to collect and screen the raw data for my study, providing descriptive statistic, frequencies, mean scores, t-tests, and characteristically analyzed group data in graphs and tables for visual interpretation (SurveyMonkey, n.d.). The raw data was then uploaded into SPSS IBM version 28 for further statistics testing. In addition, missing data was removed and negated from analytics. Thus, the Survey Monkey platform was used to organize the primary data collected from the survey tool. Further statistical analysis of the primary was done using SPSS IBM software package version 28 (IBM, n.d.).

The Research Question

Research Question: Is there a statistically significant difference in the perceived importance of enrolling in online YouTube DPP between COVID-19 social distancing compliance groups amongst survey participants?

Null Hypothesis: There is no statistically significant difference in the perceived importance of enrolling in online YouTube DPP between COVID-19 social distancing compliance groups amongst survey participants.

Alternative Hypothesis: There is a statistically significant difference in the perceived importance of enrolling in online YouTube DPP between COVID-19 social distancing compliance groups amongst survey participants.

The research question asked if there is a significant difference between SDC groups with PI of enrolling in online YouTube DPP based on common recruitment practices and behavioral expectations. The null hypothesis stated that there will be no significant difference between SDC groups amongst participants and their PI of enrolling in online YouTube DPP. The alternative indicated that there will be a difference between SDC and PI of enrolling in online YouTube DPP, relevant to address.

The variables were measured using a Likert, 5-point scale. The independent X variable represented nominal categories, whereas the Y dependent variable represented ranking scores, or numerical data. Consequently, the PI of enrolling in online YouTube videos, measured as ranking scores, ranging from 1 to 5, exemplified the Y dependent variable, and the SDC levels of participants, categorized into nominal groups, exemplified the independent X variable.

Initially descriptive statistics were used to find the mean frequencies (Wagner, 2017; Warner, 2021) for categorizing the independent X variable into SDC group levels (i.e., noncompliance, low compliance, moderately compliant, compliant, and highly compliant). Next, a one-way analysis of variance (ANOVA) relating to PI of enrolling in online YouTube DPP was conducted to determine the significance of enrolling in online YouTube DPP within each compliance group (Wagner, 2017; Warner, 2021). Yet, the final analysis of the null hypothesis depended on the data collected.

To address the null hypothesis and research question, it was necessary to assess the significant differences with a simple ANOVA of the five respective SDC groups, i.e., noncompliant, low compliant, moderately compliant, highly compliant, extremely compliant after using descriptive statistics to assign participants into corresponding groups (Kaufman, 2019; Guerrero, 2018a; Madrigal & Mannan, 2020). The inferential analysis ANOVA revealed t-distributions and the degrees of freedom needed to identify statistical significance, e.g., confirming that there is statistical difference between the five SDC groups, which warranted further evaluation when found (Kaufman, 2019; Guerrero, 2018a). To further assess the significant importance of enrolling in online YouTube DPP among participants within the five SDC groups**,** I used a one-way ANOVA again since the types of data collected was categorical and continuous. The one-way ANOVA was used to identify the significant difference between any of the five SDC groups in relation to the PI of enrolling in online YouTube DPP using the *F* ratio, i.e., a measured variance between the five SDC groups divided by the variance within the five groups relating to the PI of enrolling in online YouTube DPP (Kaufman, 2019; Guerrero, 2018a). However, the one-way ANOVA does not determine which group or groups will be significantly different. To determine which groups were statistically significant, a post-hoc test was conducted (Wagner, 2017; Warner, 2021). The post-hoc test allowed me to pinpoint which group or groups were significant corresponding to PI of enrolling in online YouTube DPP, based on compliance groups.

Frequencies and means relating to the independent variables, SDC, were individually tested to ensure the assumptions were not violated. Histograms and scatter plots were used to identify violations. In addition, individual linear regressions, or an ANOVA was performed if assumptions were not violated (Wagner 2017). Again, p-values less than 0.05 indicated statistical significance, validating the assumption that correlated PI and compliance and rejecting the null hypothesis that significance did not exist. Results were analyzed and reported with significant *p*-values less than 0.05, *F*-statistics from multi/univariate tests, and the partial n^2 effect size, or Eta squared (Wagner 2017; Warner, 2021).

Threats to Validity

The SCT may be one of several threats to the internal validity of this study. Even though SCT is a robust framework, not all constructs were used to assess participant's attitudes towards enrolling in online YouTube DPP and compliance levels in this study, lowering the internal validity of the instrument (Sharma, 2021). In addition, the constructs of the SCT functioned to associate and correlate data, not for making causations (Bandura, 1986; Anyikwa, 2018).

Another issue may be the cross-sectional approach in collecting data. Although very advantageous with limited resources and time, the internal validity of the cross-sectional approach wanes because point-in-time testing lacks continuity (Al-Hasan et al., 2020). Validity was also lost when questions were modified and adapted for integration into the study (Tsang et al., 2017). In addition, there were multiple confounding factors impacting study results beyond the scope of the study, like gender, socioeconomic status, health literacy, computer literacy, chronic diseases, and others (Mellinger & Hanson, 2020).

External threats to the validity of the study included the changing climate of social distancing norms. With fewer cases reported, and things get back to normal, perceptions and attitudes may change from prior ones (Mara & Peugh, 2020). New social conditions, such as vaccinations, may change the level of SDC level observed in the participant population, threatening the external validity of the survey instrument (Findley et al., 2021). In addition, poor response rates and personal bias response also reduced the validity of the study instrument (Findley et al., 2021).

Before I gained access to participant data or participants, I received permission from the IRB to conduct the study. This ensured that all ethical procedures were followed before conducting the study with human participants. Informed consent was obtained, and no unethical action was taken against participants throughout the study. In this case, the study was conducted online, hosted on SurveyMonkey. Individuals were given instructions and had the opportunity not to participate in the survey if they feel so inclined. Participants were given information concerning the intent and content of the survey, as well as the social implications of the study. Since the survey was carried out online and hosted on SurveyMonkey, there were no ethical concerns other than ensuring participant privacy, which was remedied through online anonymous participation.

To address ethical concerns related to recruitment, participants were presented with an anonymous link to the survey from various social media sites, such as, Facebook. Once participants connected to the online link, they were immediately taken to SurveyMonkey hosting the survey instrument. Participants anonymously accepted the terms which were outlined in the information presented to them explaining the content of the survey, the length of time to take the survey, the fact that they were able to op-out of taking the survey at any point in time whiles taking the survey, and the contribution the results of the survey would have on society.

Interviewer bias and power relationships, sometimes observed during interviewing, were mitigated by providing participants with a self-administered survey, which participants took at their convenience. Furthermore, responses were anonymously collected to protect privacy. Information was collected on SurveyMonkey, a secure platform to which only I had administrative access to. The collected data was securely downloaded onto SPSS IBM version 28 software for further analysis. For added security, I was the only individual with access to this data set, which was password protected.

The raw data was archived and secured for one year after the study. All participant information would remain confidential and anonymous during that time. Information concerning study results were disseminated once the study was completed. The information was disseminated through the same SurveyMonkey website link. After one year, the data will be destroyed.

To summarize, there were no special interest or power differentials supporting or involved in the study. Thus, there were no conflict of interest. Hopefully, the study results impact the profession towards positive social change by adding knowledge to the field.

No ethical considerations to conduct this study was sought after from the IRB, since SurveyMonkey, YouTube, and social media are considered open platforms (Pew Research Center, 2019; SurveyMonkey, n.d.). Therefore, there were no ethical concerns to consider. Participation was anonymous with the option to exit the survey at any time. No explicit information was asked other than general demographic information such as age, sex, education level, health conditions, and geographical location, which were compiled only for summative analysis.

Summary

This non-experimental, retrospective, cross-sectional study determined the PI of enrolling in online YouTube DPP during the COVID-19 pandemic based on SDC behaviors using the SCT framework. One point-in-time was measured to assess compliance and attitudes using a 5-point Likert scale. The survey tool was constructed based on three reliable and valid instruments using similar methodology (Islam et al., 2021).

The survey instrument was hosted on SurveyMonkey, where participation was voluntary and anonymous. No special administrative process was needed for participants to link, connect, and respond to the survey tool hosted on SurveyMonkey (SurveyMonkey, n.d.). A *t*-test was used in SPSS to assess the means for the independent variable, i.e., SDC level, and the dependent variable, i.e., PI of enrolling in online

YouTube DPP (IBM, n.d.). A one-way ANOVA identified the correlation between SDC levels and the PI of enrolling in online YouTube DPP during the pandemic (IBM, n.d.).

However, the study instrument was limited by internal factors; like the new survey tool created from modified survey instruments and the use of probability sampling methods to acquire participants for data collection (Li et al., 202; Mara & Peugh, 2020). The SCT also limited the internal validity of the study to correlative analysis and implications rather than possible causation analysis (Guerrero, 2018b). External factors which limited the validity include bias responses, poor recall response rates, changes pertaining to the social distancing mandates and climate of the COVID-19 pandemic, and missing data from questions with no response (Findley et al., 2021). Results from the data collected using descriptive statistics and statistical assumptions, with illustrations, graphs, charts, and tables for clarification of the outcomes using SPSS software, were presented in chapter 4.

Chapter 4: Results

Introduction

The purpose of this study was to quantify a statistically significant association between the online adult population's attitude towards enrolling in online YouTube DPP based on common enrollment practices during the COVID pandemic and their SDC level using the SCT as a framework. Healthy People 2030 (2020) indicated that the enrollment rate for national DPP was less than 2%. Therefore, more study should be done to understand why enrollment rates were so low after extensive enrollment campaigns and referral practices were implemented. My goal was to identify if an interest existed in enrolling in online YouTube DPP based on common screening and referral campaigns and practices during the pandemic due to social distancing mandates for better advocacy and promotion of type 2 DPP nationwide. This study collected data on the PI of enrolling into online YouTube DPP based on individual participant SDC groups levels, assuming that compliance levels between compliance groups could be used as an indicator for positive behavioral change in favor enrollment practices into online YouTube DPP (Li et al., 202; Mara & Peugh, 2020). Thus, the research study for the PI of enrolling in online YouTube DPP using the SCT as the framework for assessing possible behavioral change due to environmental mandates and personal beliefs about enrollment practices was proposed (Sharma, 2021). Then, the research question that follows was devised to assess the phenomenon.

Research Question

Research Question: Is there a statistically significant difference in the perceived importance of enrolling in online YouTube DPP between COVID-19 social distancing compliance groups amongst survey participants?

Hypothesis

Null Hypothesis: There is no statistically significant difference in the perceived importance of enrolling in online YouTube DPP between COVID-19 social distancing compliance groups amongst survey participants.

Alternative Hypothesis: There is a statistically significant difference in the perceived importance of enrolling in online YouTube DPP between COVID-19 social distancing compliance groups amongst survey participants.

In Chapter 4, I highlight the data collection process and provided a detailed analysis of the results based on the research question, uploaded into IBM SPSS version 28, hosted from Survey Monkey. This chapter documents the data collection process for the relative time frame, recruitment, and response rates. The descriptive statistics, assumptions, findings, and illustrations of the results are discussed and summarized for interpretation and clarity based on previous assertions grounded in evidence-based research formulated from Chapter 2 literary review. Baseline descriptive and demographic characteristics are noted in relation to external validity, sample size, and basic univariate analysis. Results are furnished with statistically significant findings and reported in tables or graphs for illustration. A final summary of the findings is also presented at the end of this chapter.

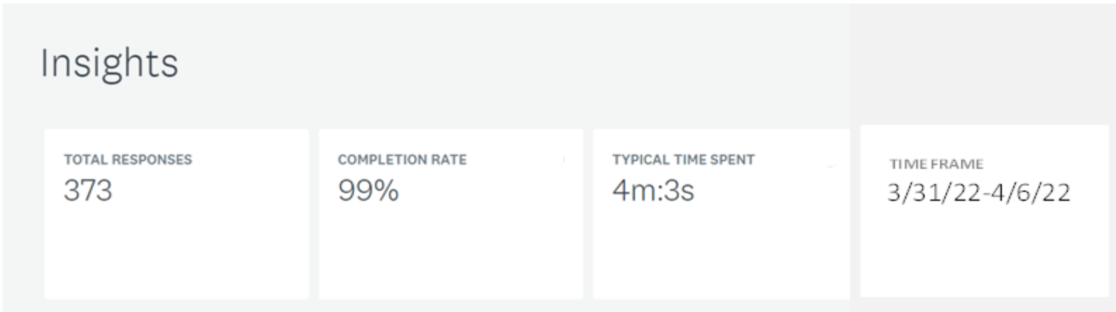
Data Collection

Recruitment, Response Rate, and Time Frame

For this study, I used the IBM SPSS version 28 G* Power Analysis software (IBM, n.b.) to tabulate the required sample size of 200 participants needed to quantify my five categorical predictor groups, representing the approximate online target U.S. adult population of over 100,000 people. The alpha level was 0.05, standard power was 0.08, and the effect size was 0.25, all common values used to confirm relevant population and sample size analysis. Participants were recruited and data was collected for the study from March 31st, 2022, thru April 6th, 2022. Then, I closed the COVID-19 Blood Sugar Wellness Survey (COVID-19BSW) hosted on SurveyMonkey after 373 participants responded to the survey (See Figure 7). However, after omitting participants which failed to meet the inclusion criteria (i.e., of appropriate age, health, and location parameters) and participants who failed to answer all of the questions, a sample size of 258 participants remained, for an overall 69% response rate. Initially, SurveyMonkey (n.b.) advised a 10-minute time frame to complete the survey; however, participants took an average of 4 minutes and 3 seconds to complete it.

Figure 7

Recruitment, Response Rates, and Time Frame



Note. Recruitment, Response Rates, and Time Frame were analyzed and reported by SurveyMonkey. Total Response represents the total participant pool before exclusion criteria was applied. Typical Time Spent represents the average time participants took to complete the survey. The Completion Rate represents the average amount of questions completed by participants before exclusion criteria was applied. Time Frame represents the recruitment and data collection period for the survey.

Sample Demographics and Characteristics

There were several exclusion criteria to consider for the study, i.e., age, location, and health conditions. Most participants were at least 23 years old, indicated by the mode value. The average age for participants was 42 years (SD = 16), indicated by the mean value. The minimum age was 18 and the maximum age was 92 (see Table 11). Note that only online adults over 18 years of age were recruited.

Table 11

Age Demographics and Characteristics

N	Mean	Mode	Std. deviation	Minimum	Maximum
258	41.77	23	16.072	18	92

Participants volunteered from all over the United States, satisfying the exclusion/inclusion criteria for U.S. participation only, where N = 258. There were also health conditions to consider for inclusion/exclusion criteria. Participation was limited to nondiabetic and nonpregnant or lactating women, of which all other conditions were excepted. Refer to Table 12.

Table 12

Health Demographics and Characteristics

Conditions	N=258	Frequency	Percent
Heart disease		26	10.1
Cancer		6	2.3
Lung disease		7	2.7
High blood pressure		57	22.1
Obesity		41	15.9
Other		50	19.4
None		130	50.4

Note. Only participants with the above conditions were selected for the study.

Education and gender were used as parameters to safeguard the equity and diversity of the selected participants. For instance, most individuals either had a high school diploma or a bachelor’s degree, and about 60% of the participants were female. Refer to Figure 8 and Table 13.

Figure 8

Educational Demographics and Characteristics

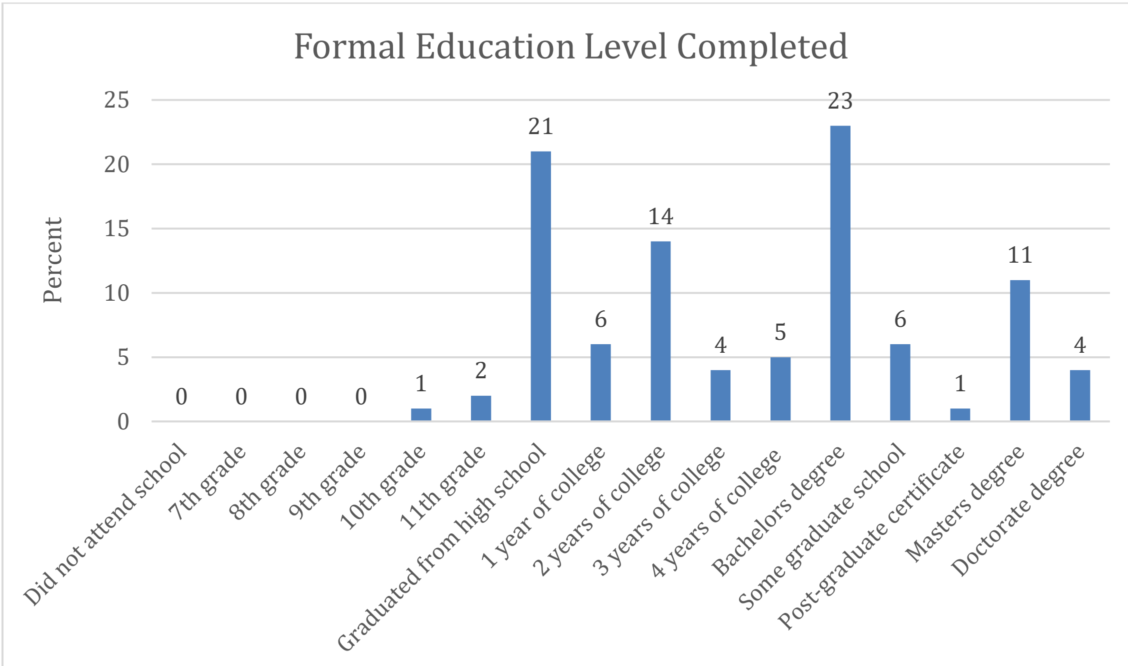


Table 13

Gender Demographics and Characteristics

Gender	N	%
Female	160	62.0%
Male	95	36.8%
Other	3	1.2%

In short, the sample population's response to the SDC and PI questions presented in Table 14 and 15 indicated that staying home when feeling sick (M = 4.29, SD = .978, 57%) and covering ones mouth when sneezing (M = 4.64, SD = .787, 78%) represented the highest responses for the SDC questions. And, face-to-face doctor referrals (M = 3.94, SD = 1.086, 37%) and knowing about insurance coverage (M = 3.55, SD = 1.287, 31%) were the highest absolutely important responses for the PI questions. Refer to Table 14 and 15. Note, all responses were evaluated from a mean range of 1 to 5.

Table 14

SDC Response Demographics and Characteristics

N=258 Total 10 questions	Mean range 1 to 5	Std. deviation	Never	Rarely	Sometimes	Often	Always
Do you wash your hands frequently during a typical day to stop the spread of COVID-19?	4.29	.890	1.9%	2.7%	9.3%	36.0%	50.0%
Do you stay home when you feel sick to stop the spread of COVID-19?	4.29	.978	2.3%	2.3%	16.3%	21.7%	57.4%
Do you stay indoors when the CDC recommends it to stop the spread of COVID-19?	3.89	1.172	6.2%	5.4%	20.9%	27.9%	39.5%
Do you keep 6-feet distances in public to stop the spread of COVID-19?	3.88	1.035	3.5%	5.0%	24.0%	34.9%	32.6%
Do you wear a face mask in public to stop the spread of COVID-19?	3.86	1.282	7.4%	8.9%	18.6%	20.2%	45.0%
Do you follow the latest health safety news about the spread of COVID-19?	3.83	1.220	6.6%	7.4%	22.5%	23.6%	39.9%
Do you wash/wipe off groceries that you brought home from the store to stop the spread of COVID-19?	2.79	1.371	22.9%	22.5%	23.3%	15.9%	15.5%
Do you cover your mouth when sneezing or coughing to stop the spread of COVID-19?	4.64	.787	1.2%	1.9%	6.6%	12.0%	78.3%
Do you cook your own meals to stop the spread of COVID-19?	3.69	.993	3.5%	6.6%	29.1%	39.5%	21.3%

Do you shower after going outside to stop the spread of COVID-19?	3.00	1.342	16.7%	20.5%	28.7%	14.7%	19.4%

Table 15

PI Response Demographics and Characteristics

N=258 Total 20 questions	Mean range 1 to 5	Std. deviation	Not important	A little important	Important	Very important	Absolutely important
Committing 20 to 40 minutes for online sessions:	2.94	1.121	12.8%	19.0%	38.4%	21.3%	8.5%
Being able to use smartphones or other devises to participate:	3.56	1.212	7.4%	10.9%	27.9%	26.0%	27.9%
Being able to subscribe to online YouTube DPP channels:	2.90	1.171	13.6%	22.9%	34.5%	18.6%	10.5%
Getting frequent updates about online YouTube DPP:	2.88	1.208	16.7%	19.0%	34.5%	19.4%	10.5%
Being able to buy what you saw on YouTube DPP:	2.83	1.273	19.0%	20.9%	31.0%	16.3%	12.8%
Learning groups:	2.64	1.159	20.5%	23.6%	32.6%	17.4%	5.8%
Learning different exercise regiments:	3.33	1.106	8.5%	11.2%	32.6%	34.5%	13.2%
Learning personal control skills:	3.45	1.160	7.8%	12.0%	27.1%	33.7%	19.4%
Working with a motivational coach:	2.88	1.233	15.9%	23.3%	28.7%	20.9%	11.2%
Learning more about diabetes recipes:	3.29	1.222	10.5%	13.2%	32.2%	24.8%	19.4%

An online referral from a credible YouTube channel:	2.24	1.186	35.3%	26.4%	21.3%	12.8%	4.3%
A virtual appointment referral from your primary doctor:	3.54	1.137	6.2%	10.9%	28.3%	32.2%	22.5%
A face-to-face referral from a friend:	2.79	1.103	12.0%	30.2%	31.4%	19.4%	7.0%
An online referral from a family member:	2.79	1.159	15.5%	26.7%	27.9%	23.3%	6.6%
A face-to-face referral from your primary doctor:	3.94	1.086	4.7%	5.0%	19.0%	34.5%	36.8%
Knowing the upfront cost of online YouTube DPP:	3.38	1.351	13.2%	12.0%	25.6%	21.7%	27.5%
Knowing your personal risk for developing diabetes and prediabetes:	3.66	1.164	7.0%	7.8%	25.6%	32.2%	27.5%
Knowing your blood sugar, or glucose level:	3.64	1.125	6.2%	7.4%	27.9%	32.9%	25.6%
Knowing if the online YouTube DPP is covered by your insurance:	3.55	1.287	9.3%	11.6%	24.0%	24.4%	30.6%
Knowing about the advantages and disadvantages of blood sugar, or glucose medicine:	3.58	1.141	6.2%	9.3%	29.5%	30.2%	24.8%

Tools for the Population of Interest

The SCT was used to formulate cognitive questions to collect credible ideological/philosophical responses from participants concerning my study hypothesis, null, and alternative questions (Anyikwa, 2018; Bandura, 1986; Mensa-Kwao et al., 2019; Mensa-Wilmot et al., 2020). The five environmental factors questions, i.e., SDC government mandates, and the five personal factors questions, i.e., SDC personal measures, both denoted the independent variable, or SDC level construct of the study framework (Bandura, 1986). The four behavioral response subgroups, i.e., referrals, screening, activities, and commitments, consisting of five questions per subgroup represented the dependent variable, or PI of enrolling into YouTube DPP construct for the study framework (Bandura, 1986). Therefore, responses collected from the SDC level construct and the PI of enrolling into YouTube DPP construct were required to validate the internal integrity of the survey instrument by Cronbach's alpha (Anyikwa, 2018; Bandura, 1986; Mensa-Kwao et al., 2019; Mensa-Wilmot et al., 2020).

Cronbach's Alpha

The Cronbach's alpha coefficients were used to confirm the internal validity of the COVID-19BSW instrument developed from the SCT framework in my study and helped me determine whether to move forward with analyzing the data collected from the survey instrument (see Table 16).

Table 16

Cronbach's Alpha Reliability Ranges

Coefficient of Cronbach's Alpha	Reliability level

Greater than 0.90	Excellent (>0.95 is subjective to redundancy but desirable for clinical practice)
0.80-0.89	Good
0.70-.079	Good and acceptable
0.60-69	Questionable or poor
0.50-0.59	Unacceptable

Note. This table was constructed from work cited from, Vet, Henrica C. W. de, Lidwine B. Mokkink, David G. Mosmuller, and Caroline B. Terwee. "Spearman-Brown Prophecy Formula and Cronbach's Alpha: Different Faces of Reliability and Opportunities for New Applications." Journal of Clinical Epidemiology 85 (May 2017): 45–49. https://doi.org/10.1016/j.jclinepi.2017.01.013.

Acceptable reliability results greater than 0.90 for Cronbach's alpha were considered favorable for clinical practice, according to Vet et al. (2017). However, results above 0.70 were acceptable as well (See table 15.). Since the SDC and PI constructs differed conceptually, separate five-point Likert scales and Cronbach's alpha analysis were administered according to the considerations outlined by Leppink and Pérez-Fuster (2017) to confirm the internal validity of the data collected.

Reliability Statistics for SDC

Again, the internal reliability for the data collected on the 10 theoretical construct questions for SDC in the study were tabulated after exclusion parameters were applied to the total participant pool of 373, reducing the number of research cases to 258. A 0.86 Cronbach's alpha was derived from the 10 standardized questions and 258 cases, which confirmed the internal reliability of the data collected for the SDC theoretical construct in the study. Table 17 highlights both the participant cases or number of participants selected for the study and the 10 theoretical questions used to tabulate the Cronbach's alpha.

Table 17

SDC Reliability Statistics

N=258 Cronbach's Alpha	Cronbach's Alpha based on standardized items	Mean	Variance	Std. deviation	N of items
.864	.868	38.17	56.606	7.524	10

Note. The internal reliability was based on 258 cases or participants after exclusion criteria and 10 SDC items or questions which were all corrected for missing responses.

Reliability Statistics for PI

Again, the internal reliability for the data collected on the 20 theoretical construct questions for PI in the study were tabulated after exclusion parameters were applied to the total participant pool of 373, reducing the number of research cases to 258. A 0.94 Cronbach's alpha was derived from the 20 standardized questions and 258 cases, which confirmed the internal reliability of the data collected for the PI theoretical construct in the study. Table 18 highlights both the participant cases or number of participants selected for the study and the 20 theoretical questions used to tabulate the Cronbach's alpha.

Table 18

PI Reliability Statistics

N=258 Cronbach's	Cronbach's Alpha based on standardized	Mean	Variance	Std. deviation	N of items

Alpha	items				
.941	.941	63.82	262.539	16.203	20

Note. The internal reliability was based on 258 cases or participants after exclusion criteria and 20 PI items or questions which were all corrected for missing responses.

Thus, the internal validity of the data collected was confirmed as reliable based on the Cronbach's alpha evaluated. Therefore, it was appropriate for me to perform a one-way ANOVA to statistically analyze the data collected and answer the research question.

Results

Descriptive Statistics

SDC Statistics

Based on the descriptive statistics for SDC groups and the PI of enrolling into YouTube DPP, there were some differences observed between the means for each group (see Table 19). The Noncompliant group was n = 4, 1.6%, SE = 0.8, 95% CI [0.4, 3.1]. The Low Compliance group was n =13, 5.0%, SE = 1.4, 95% CI [2.7, 8.1]. The Compliant group was n = 57, 22%, SE = 2.5, 95% CI [17.1, 27.1]. For the Highly Compliant group, n = 105, 40.7%, SE = 3.0, 95% CI [34.9, 46.5]. Finally, the Always Compliant group was n = 4, 30.6%, SE = 2.7, 95% CI [25.6, 36.0].

Table 19

Nominal Independent Variable: SDC Five Categorical Descriptive

SDC categories				95% Confidence interval	
N=258	N	%	Std. error	Lower	Upper
Noncompliant	4	1.6%	.8	.4	3.1
Low compliance	13	5.0%	1.4	2.7	8.1
Compliant	57	22.1%	2.5	17.1	27.1

Highly compliant	105	40.7%	3.0	34.9	46.5
Always compliant	79	30.6%	2.7	25.6	36.0

PI Statistics

Based on the descriptive statistics for SDC groups and the PI of enrolling into YouTube DPP, there were little differences observed between the means for each group (see Table 20). The Noncompliant group mean value was 53, SD = 23, 95% CI [17, 89]. The Low Compliance group mean value was 47, SD = 16, 95% CI [38, 57]. The Compliant group mean was 60, SD = 14, 95% CI [57, 64]. The mean value was 64, SD = 15, 95% CI [60, 67] for the Highly Compliant group. Finally, the Always Compliant group had a group mean value of 69, SD = 16, 95% CI [66, 73].

Table 20

Continuous Dependent Variable: PI of Enrolling into YouTube DPP Descriptive

	N	Mean	Std. deviation	Std. error	95% Confidence interval for mean		Minimum	Maximum
					Lower bound	Upper bound		
Noncompliant	4	53.00	22.58	11.29	17.06	88.93	20.00	71.00
Low compliant	13	47.23	15.81	4.38	37.67	56.78	20.00	72.00
Compliant	57	60.49	14.38	1.90	56.68	64.30	20.00	98.00
Highly compliant	105	63.98	15.41	1.50	61.00	66.96	20.00	96.00
Always compliant	79	69.28	15.86	1.78	65.72	72.83	24.00	100.00
Total	258	63.82	16.20	1.01	61.83	65.80	20.00	100.00

Note. Statistics for each analysis are based on cases with no missing data for any variable in the analysis.

Statistical Assumption

Assumptions associated with the one-way ANOVA model includes having no significant PI scores visible as outliers in the boxplot after placement into the SDC categorical groups, as seen in Figure 9. Having outliers violates one of the model assumptions. However, according to Warner (2021), having outliers does not always negate the outcome of the ANOVA analysis. In some cases, the impact of having outliers in the ANOVA model are negligible, due to the sizes of the sample and the confidence interval of the group that the outliers belong to and the values of the outliers scores (Wagner, 2017; Warner, 2021). For instance, if the score values of the outliers fall just above or below the confidence intervals of larger sample groups, then the impact to the overall ANOVA analysis would be minimal in respect to outcomes without any outliers. This means that removing the outlies would not change the outcome. So, no action to remove outliers was warranted for my data because the outliers fall just outside the confidence intervals of large sample groups. The Q-Q plots test the normality assumption of the model, of which, the PI scores within each categorical group must fall within proximity of the normality line to validate the assumption. Refer to Figure 10, 11, 12, 13, and 14. Based on the observed Q-Q plots of my data, all groups validated the assumption. The final assumption, the Levene test, determines the homogeneity of the variances. For instance, the Levene test with a p-value above 0.05 ($p = 0.664$; refer to Table 21) validated the homogeneity of variance for the SDC categorical groups (Wagner, 2017; Warner, 2021). Thus, the statistical assumptions were substantiated enough to run the one-way ANOVA model analysis for the independent categorical variable, SDC and dependent continuous variable, PI (IBM, n.d.).

Figure 9

Boxplot for validating assumptions of outliers

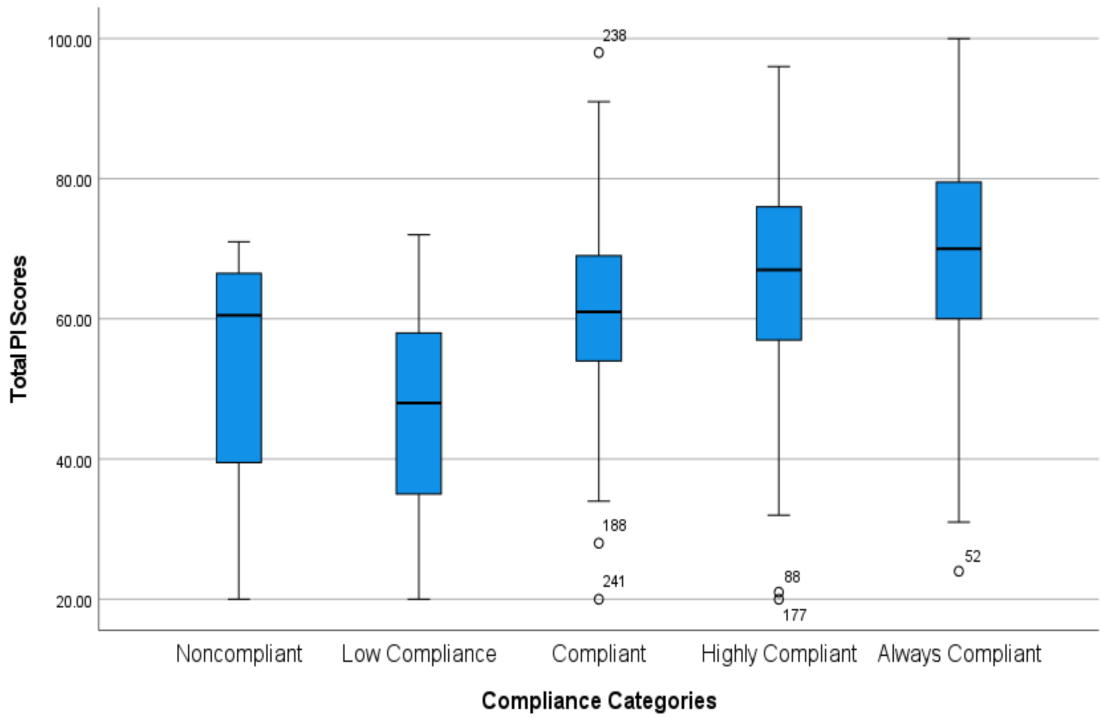


Figure 10

Q-Q Plot: SDC Noncompliant PI Scores

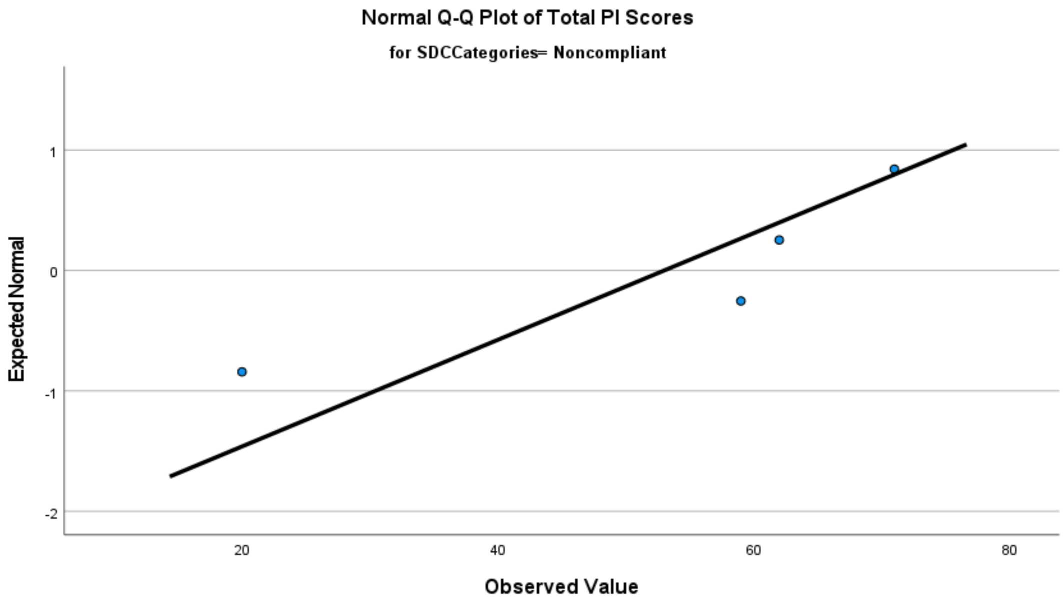


Figure 11

Q-Q Plot: SDC Low Compliance PI Scores

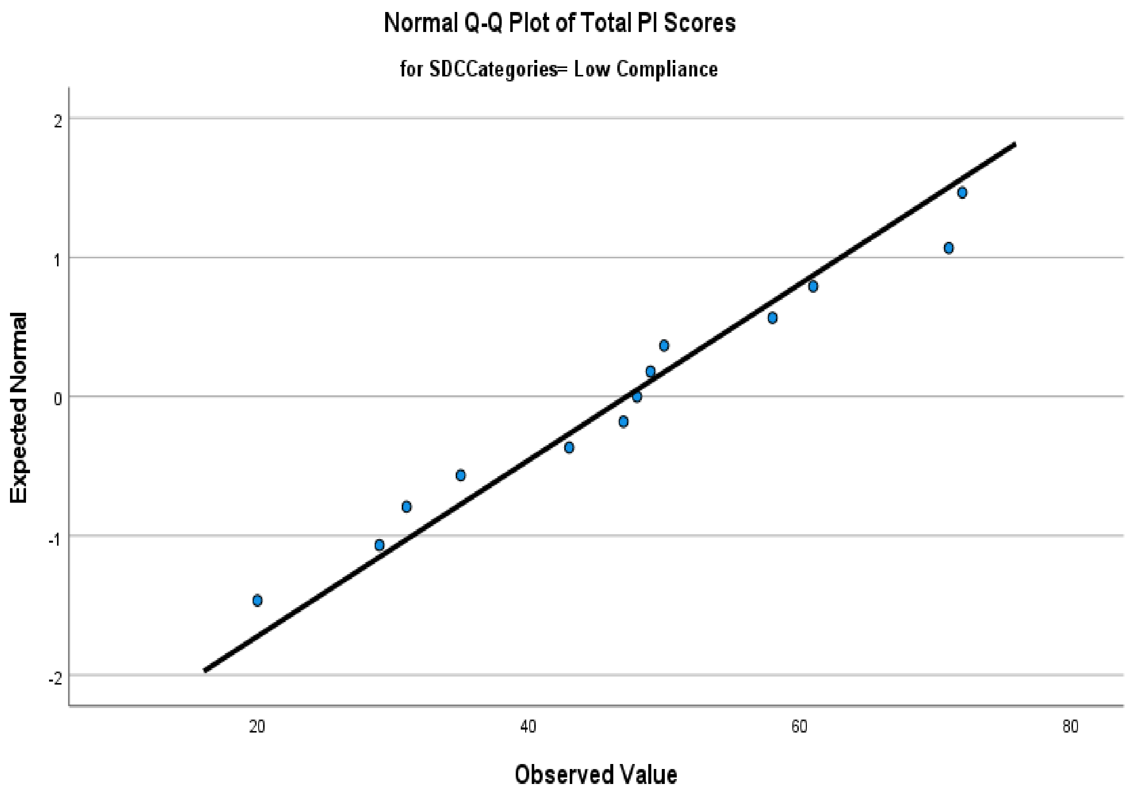


Figure 12

Q-Q Plot: SDC Compliant PI Scores

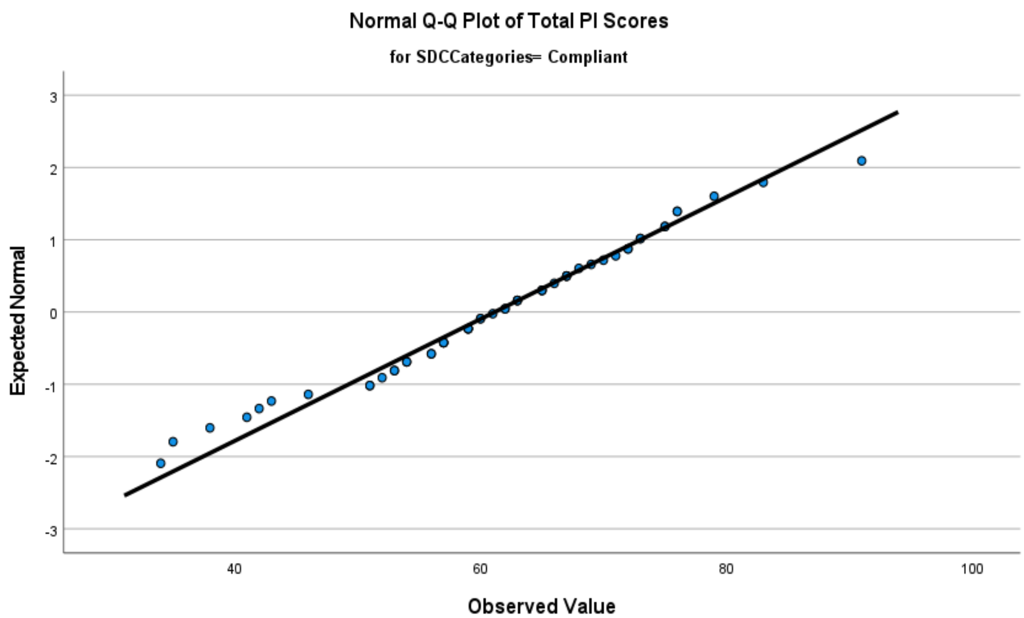


Figure 13

Q-Q Plot: SDC Highly Compliant PI Scores

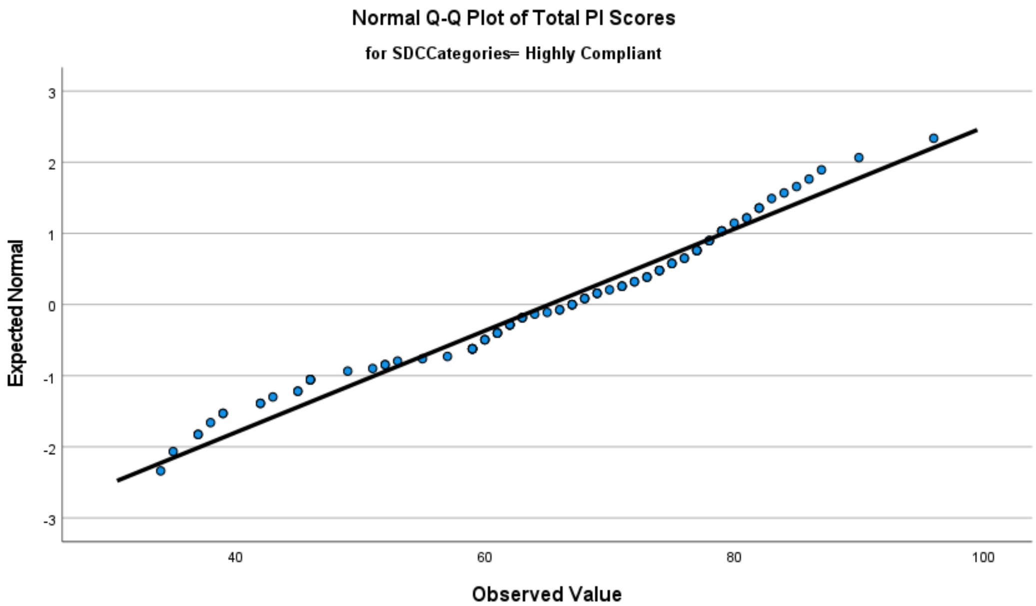


Figure 14

Q-Q Plot: SDC Always Compliant PI Scores

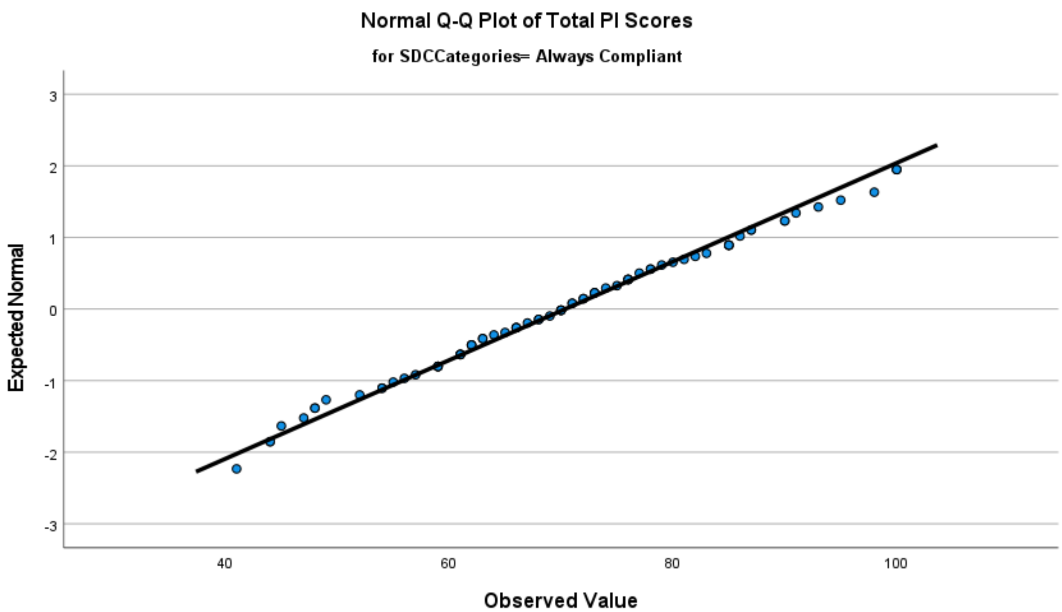


Table 21

Test of Homogeneity of Variances

		Levene statistic	df1	df2	Sig.
Total PI scores	Based on mean	.598	4	253	.664
	Based on median	.346	4	253	.847
	Based on median and with adjusted df	.346	4	235.517	.846
	Based on trimmed mean	.547	4	253	.701

Research Question

Research Question: Is there a statistically significant difference in the perceived importance of enrolling in online YouTube DPP between COVID-19 social distancing compliance groups amongst survey participants?

Statistical Findings

The PI scores of enrolling in online YouTube DPP was significantly and statistically different between COVID-19 SDC participant groups, $F (4, 253) = 7.36$, $p < .001$. There was also a small effect size observed, $\eta^2 = 0.104$, 95% CI [0.034, 0.167]. Refer to Table 22 and 23, *One-way ANOVA* and *ANOVA Effect Sizes for PI*. The PI value scores increased on average between the SDC categories as observed by the boxplot (refer to Figure 9). Thus, Tukey post hoc test was conducted to identify the mean differences between groups.

The means, standard deviations, standard errors, and p-values between groups increased or decreased as depicted here (see Table 24). Noncompliant (M = 53, SD = 22.58) to Low Compliance (M = 47, SD = 15.81) had a mean decrease of -5.8, SE = 8.8, and was not statistically significant (p = .966). Low Compliance (M = 47, SD = 15.81) to Compliant (M = 60, SD = 14.38) had a mean increase of 13.3, SE = 4.6, and was statistically significant (p = .044). Compliant (M = 60, SD = 14.38) to Highly Compliant (M = 64, SD = 15.41,) had a mean increase of 3.5, SE = 2.5, and was not statistically significant (p = .646). Finally, Highly Compliant (M = 64, SD = 15.41,) to Always Compliant (M = 69, SD = 15.86,) had a mean increase of 5.3, SE = 2.3, and was not statistically significant (p = .148). However, Low Compliance to Compliant, Highly

Compliant, and Always Compliant had statistically significant mean increases of 13.3 (SE = 4.8), 16.8 (SE = 4.5), and 22.0 (SE = 4.6), respectively, with p = .044, p = .003, and p < .001, respectively. Consequently, Compliant to Always Compliant had a 8.8, SE = 2.7, mean increase, which was statistically significant (p = .011).

Table 22

One-way ANOVA

ANOVA total PI scores	Sum of squares	df	Mean square	F	Sig.
Between Groups	7034.049	4	1758.512	7.361	<.001
Within Groups	60438.389	253	238.887		
Total	67472.438	257			

Table 23

ANOVA Effect Sizes for PI

			95% Confidence interval	
		Point estimate	Lower	Upper
Total PI scores	Eta-squared	.104	.034	.167
	Epsilon-squared	.090	.019	.154
	Omega-squared Fixed-effect	.090	.019	.154
	Omega-squared Random-effect	.024	.005	.043

Note. Eta-squared and Epsilon-squared are estimated based on the fixed-effect model.

Table 24

Tukey (HSD) Dependent Variable Multiple Comparisons Post Hoc Tests for Total PI Scores

					95% Confidence interval	
(I) Compliance categories	(J) Compliance categories	Mean difference (I-J)	Std. error	Sig.	Lower bound	Upper bound
Noncompliant	Low compliance	5.769	8.837	.966	-18.511	30.050
	Compliant	-7.491	7.994	.882	-29.457	14.474

	Highly compliant	-10.981	7.873	.632	-32.615	10.653
	Always compliant	-16.278	7.921	.243	-38.042	5.485
Low compliance	Noncompliant	-5.769	8.837	.966	-30.050	18.512
	Compliant	-13.260*	4.750	.044	-26.313	-.2083
	Highly compliant	-16.750*	4.544	.003	-29.236	-4.264
	Always compliant	-22.047*	4.625	<.001	-34.758	-9.338
Compliant	Noncompliant	7.491	7.994	.882	-14.474	29.457
	Low compliance	13.260*	4.750	.044	.208	26.313
	Highly compliant	-3.489	2.543	.646	-10.476	3.497
	Always compliant	-8.787*	2.686	.011	-16.167	-1.407
Highly compliant	Noncompliant	10.980	7.874	.632	-10.653	32.615
	Low compliance	16.750*	4.544	.003	4.264	29.236
	Compliant	3.489	2.543	.646	-3.4967	10.476
	Always compliant	-5.297	2.302	.148	-11.622	1.027
Always compliant	Noncompliant	16.278	7.921	.243	-5.485	38.042
	Low compliance	22.047*	4.626	<.001	9.338	34.758
	Compliant	8.787*	2.686	.011	1.407	16.167
	Highly compliant	5.297	2.302	.148	-1.027	11.622

Note. * The mean difference is significant at the 0.05 level.

Summary

There were five SDC participant categories: Noncompliant (*n* = 4), Low Compliance (*n* = 13), Compliant (*n* = 57), Highly Compliant (*n* = 105), and Always Compliant (*n* = 79). The boxplot indicated that there were PI score outliers, however, it was determined to have little impact on outcomes; the Q-Q plots revealed that the data was distributed normally for SDC groups; and the Levene's test, p = .664, validated the homogeneity of variances for SDC groups. Thus, the tests validated all but one assumption. Since there was a statistically significant p-value of <.001, for the group means, I rejected the null hypothesis and accepted the alternative hypothesis. To summarize the findings of the one-way ANOVA conducted for my research question, there was a statistically significant difference, $F(4, 253) = 7.36$, $p < .001$, in the PI of enrolling in online YouTube DPP between COVID-19 SDC groups amongst survey participants.

Therefore, the implication asserting that individuals who are more compliant would be more interested in enrolling into YouTube DPP to stay connected with the healthcare community was correct. Yet, there must be more studies done to substantiate this type of assumption. In chapter 5, I investigated the assumptions of the research question and expanded on recommendations for future studies, whiles incorporating the results into probable practice measures.

Chapter 5: Interpretations, Recommendations, and Conclusions

Introduction

The purpose of this study was to determine the PI of enrolling into YouTube DPP during COVID in individual participants with different levels of SDC behavior. This study was performed to identify participants' SDC behavior and then associate their behavioral compliance response with their PI of enrolling into YouTube DPP, as described as plausible outcomes based on the SCT framework by Wulfert (2019) and Mara and Peugh (2020). Since there was a statistically significant difference in PI scores within compliance groups, individual participants with above average levels of SDC may be more favorable to online YouTube DPP (Bavel et al., 2020; Kocyigit et al., 2020). It may be conceivable to market YouTube DPP to individuals with responsive compliance behaviors to improve the low enrollment rates into National DPP through YouTube.

Nature of Study

This study was a quantitative, cross sectional, retrospective analysis of the PI of enrolling into online YouTube DPP during COVID-19 due to the social distancing mandate and based on participant SDC levels. The SCT was used as a framework for the study. The theory allowed me to establish measurable parameters for the independent variable, i.e., SDC and the dependent variable, i.e., the PI of enrolling in YouTube DPP during COVID-19. SDC represented the environmental factors as well as personal beliefs towards social distancing (Bandura, 1986; Sharma, 2021). The PI of enrolling into DPP represented the behavior or the attitude in question (Bandura, 1986; Sharma, 2021).

Study Significance

Since YouTube is an excellent learning tool that overcomes health literacy issues, it makes sense to use this type of platform to promote better health through enrollment into national DPP (Madrigal & Mannan, 2020; Mensa-Wilmot et al., 2020; Nye, 2020). It was assumed that the isolation created by the pandemic has increased online communications and interest in online health related content as the public attempted to reconnect to the medical community (Mensa-Wilmot et al., 2018; Plohl & Musil, 2021; Ritchie, 2020). This included using YouTube to obtain relevant health information. Thus, it was assumed that those who were highly compliant were more motivated to remain healthy and likely to engage in health-related programs online, in this case, online YouTube DPP. With this assumption, a campaign to improve the less than 2% enrollment rate into national DPP could be launched targeting compliant populations during pandemics (Ackermann et al., 2019; Banerjee et al., 2020). Therefore, the study was conducted to understand the phenomenon behind the assumption that compliance behavior among participants could be used to determine the PI towards enrollment into online YouTube DPP. These individuals would be targeted for enrollment into online YouTube DPP to improve national DPP enrollment rates and reduce diabetic incidence.

Key Findings

Findings, where N = 258 participants, indicated that there were statistically significant differences between participant compliance groups and their PI scores to enroll into YouTube DPP, with more compliant groups showing higher interest in enrollment in online YouTube DPP. The average IP mean score for the total participant population was about 64 (SD = 16) out of a range of 20 to 100 points. About *n* = 105 of the participant pool were highly compliant. While about *n* = 79 of participants responded to be always compliant. PI percentages for enrollment practices were the highest for face-to-face referrals, self-control skills, the ability to access YouTube DPP from their smart phone, and all screening practice questions were perceived as important overall. Refer to Table 18. In addition, enrollment information about recipes and exercise regiments were more important than coaching, group activities, and allocating time towards program activities, i.e., all with low PI percentages, and were not considered key factors for enrollment. Yet, upfront cost, insurance coverage, personal risk, elevated glucose levels, and treatment options were what participants responded would motivate them the most to enroll into YouTube DPP overall. Refer to Table 18.

Interpretation of the Findings

There were several findings that supported the Chapter 2 peer-reviewed literature that may extend the knowledge of the discipline. The most important finding implied that SDC and PI variables may be associated, further validating the SCT used as the framework for my research study (Bavel et al., 2020; Kocyigit et al., 2020). Based on the observed ANOVA results, there were slight differences between the participant's SDC groups and PI scores. Results revealed that participants were slightly motivated to enroll into online YouTube DPP based on their compliance to social distancing mandates and personal measures to not contract COVID. According to Banerjee et al. (2020), there should have been an increased favorability for the participants with high standards towards social distancing during the pandemic. This was my conclusive observation for the participants in this study based on the ANOVA analysis. The assumption that isolation due to social distancing mandates and personal measures would increase favorability towards enrolling into online YouTube DPP was captured here in these findings, even if the effect size ($\eta^2 = 0.104$) for the differences between the groups were small in comparison to the PI scoring scale. To clarify, the PI mean score for the total participant population was 64 (SD = 16) and only 69 (SD = 16) for the highest group mean on a PI scale of 20 to 100.

According to the SCT, compliance levels would differ and could be categorized into noncompliant, little compliance, compliant, highly compliant, and always compliant groups due to personal beliefs (Mensa-Wilmot et al., 2020). Their PI, or behavior, to enroll in online YouTube DPP would depend on those personal belief factors, which were influenced by social distancing mandates, i.e., an environmental factor (Banerjee et al., 2020; Clark et al., 2020). Thus, participants with higher compliance levels would perceive the importance of enrolling into YouTube DPP more so than participants with lower compliance levels (Mara & Peugh, 2020). The results revealed that there were statistically significant differences in the PI scores amongst participant compliance groups. To clarify, the environmental and personal factors impacted the participant's PI of enrolling into YouTube DPP. But due to the small effect size, one could argue that other environmental factors, such as loss of income, fear of displacement, and contracting COVID could have been more pressing concerns that took precedence over the PI of preventive diabetic measures, i.e., covariances. Further study should be conducted to fully substantiate my claim.

Limitations of the Study

To begin, the COVID-19BSW was constructed to collect participant consent, demographics, and research responses. First, consent to participate in the study consisted of asking one yes/no question to participate in the survey and ensure ethical standards issued by the IRB were met. Even though that added to the trustworthiness of the instrument, it did not guarantee participation. Then, five demographic matrix questions regarding age, education levels, health conditions, sex, and location characteristics were constructed to rule out selection bias and recruit participants from the online U.S. adult population, limiting type 1 and 2 diabetic selections from the participant pool.

For example, age was used to exclude participants under 18 years old. Health condition parameters were used to exclude lactating mothers and participants with type 1 and 2 diabetes. Location was used to ensure that only U.S. residents applied equally from every state. Sex and education parameters were configured to safeguard diversity within the online participant population selected. Finally, 30, five-point Likert scale research questions were devised to analyze five SDC levels and PI scores using a one-way ANOVA (Mellinger & Hanson, 2020; Vet et al., 2017), creating a total of 36 questions (See Appendix B). The COVID-19BSW survey was hosted on SurveyMonkey, and after collecting data devised specifically for answering the research question, the data set was downloaded to IBM SPSS version 28.

In addition, participants were limited from responding freely since they were given close-ended questions for self-reporting. Consequently, self-reported questionnaires tend to be bias because participants may feel pressured to respond according to what they consider to be socially acceptable (Mellinger & Hanson, 2020). Yet, I trusted that participants' responses were given to their best ability, considering that the response rate was about 99%. Also, this survey collected responses anonymously to mitigate self-reporting bias and increase the internal reliability of data collected (Tsang et al., 2017). Furthermore, multiple questions in tandem, i.e., five-point Likert scale questions, about related concepts were used to mitigate bias responses as well (Mellinger & Hanson, 2020; Tsang et al., 2017).

Another limitation was the SCT framework design. According to Bandura (1986), the theory would limit my application to identifying participant PI scores without formulating predictions or substantiating cause. However, the SCT framework allowed me to identify PI scores to answer the study question and hypothesis. Again, the Cronbach's alpha for the instrument was between 0.85-0.95 when evaluated. Therefore, the study was acceptable for clinical purposes, where the evaluation of 0.9 and above was most favorable (Leppink & Pérez-Fuster, 2017; Vet et al., 2017). Note that anything over 0.98 would be considered questionable due to duplication. As a result, the instrument was valid and reliable, supporting the credibility of this study in the clinical regard.

Recommendations

The SCT theory helped strengthen the internal validity of this study because I was able to use the constructs to devise five-point Likert scale questions which pinpointed the nature of my study assumptions with a direct line of close-ended questioning (Shamizadeh et al., 2019; Zhou et al., 2020). With little time and resources at my disposal, this theoretical model was most appropriate, and I recommend using the SCT for future applications in studies (Mohebbi et al., 2019). For example, I was able to collect credible data with the SCT corresponding to the attitudes and perceptions of participants to effectively answer the research question and hypotheses, whiles using Cronbach's alpha coefficients for internal reliability validation (Guerrero, 2018; IBM, n.d.; Querido et al., 2021). Using SurveyMonkey as a host for the survey instrument was also advantageous. SurveyMonkey was an effective platform to reach the online adult target population using social media, i.e., like Facebook, Twitter, YouTube, and others (SurveyMonkey, n.d.). However, I also recommend using the Walden University website in the future as an academic population resource (Walden University, 2021).

Again, this study was a quantitative, cross sectional, five-point Likert scale survey study, with close-ended questions for expediency. However, future studies should include some open-ended questions to improve response bias (Mohebbi et al., 2019). Also, a longitudinal survey would cut down selection bias and improve the internal and external validity of the data collected from participant responses. Collecting data at one-point-in-time was convenient when faced with time and resource constraints, but the data collection process spanning over different time intervals, as performed in a longitudinal survey study, would be more robust, and thus recommended. Finally, if feasible, future researchers should use a qualitative method and the HBM to quantify behavior predictions with observed attitudes, since the SCT was limited to identification of current perceptions without strong predictive value (Sharma, 2021).

Implications

Positive Social Change: Societal/Policy

The implications of the findings in this study could be used to improve national policy and guidelines provided by the CDC impacting enrollment practices into YouTube and national DPP. Positive impact for such social change can be promoted and employed from understanding the PI of DPP enrollment practices during unfavorable social climates, like the COVID-19 pandemic (Mara & Peugh, 2020). The evidence from this study indicate that the PI of enrollment practices was not incumbered by social distancing mandates or isolation, were the p-value was less than 0.05. In fact, participants PI scores of enrolling into online YouTube DPP slightly increased as the level of compliance behavior increased between participant groups. There were significant differences in the importance between the different enrollment practices which remain consistent with previous studies by Mensa-Wilmot et al. (2020) and Ackermann et al. (2019), to name a few. Politicians, law makers, and clinicians can use this study results to propose positive social change in diabetes prevention by focusing on enrollment practices into nationwide DPP without being concerned about whether enrollment efforts will be hindered by the pandemic climate. For instance, participants indicated that enrollment practices should include more information about program cost, insurance coverage, self-control skills, exercise regiments, and recipes. Ackermann et al. (2019) stated that clinician reimbursement plans were also vital for enrollment into programs since referrals were the primary gateway for enrollment, and my study findings support this claim, were 36.8% (3.9, SD = 1.1) of participant still favor face-to-face doctor referrals for enrollment into

YouTube DPP. The study showed that 30.6% (3.6, SD = 1.3) of participants were interested in understanding more about insurance options during enrollment and 27.9% (3.6, SD = 1.2) were concerned about accessing the program through smartphone devices. Thus, by focusing on impacting DPP enrollment policies and practices, diabetes prevention and self-management programs could be more effective.

Theoretical Implications

As mentioned, the SCT was used as the framework for this study, and my findings (i.e., $F(4, 253) = 7.36$, $p < .001$) do confirm and validate the theory as Bandura (1986) intended. Results indicated that participants did perceive the importance to enroll into YouTube DPP during the new social climate from personal compliance measures and mandates as theorist like Zhou et al. (2020) and Shamizadeh et al. (2019) suggested. These theorists, like Sharma (2021), said that the three major constructs help practitioners understand attitudes toward potential behavioral intent that already exist. Evidence from my data supports these claims.

Recommendations for Practice

So, my findings indicate that providing the community with better insurance coverage options, strengthening doctor referral campaigns, and presenting information about cost, personal risk, and treatment options through smartphones would help promote positive social change in communities as advised by Healthy People 2030, and the CDC (2020) concerning national DPP. In addition, programs should focus on improving self-control skills and provide recipes that fit into diverse lifestyles. According to this study results, these enrollment practices were perceived to be important towards enrolling into

YouTube DPP based on one's compliance level during the pandemic. Again, my findings support Ackermann et al. (2019), Holliday et al. (2019), and Venkataramani et al. (2019), who all claimed that improving these enrollment practices would be most appropriate towards increasing enrollment into DPP nationwide.

Conclusion

The assumption that the COVID-19 social distancing mandate motivates the PI of recruitment practices into YouTube DPP among participants was proven in my findings, which provided some clarification of the research done by Nye (2020), Plohl and Musil (2021), and Yin et al. (2020) of whom already supported this assumption. Researchers and clinicians must be reminded that assumptions are not based on facts, and research must be done to confirm or validate assumptions entrenched in clinical practice and culture. If not, needless bias in favor of these common assumptions could hinder the advancement of clinical practice, or the interpretation of sound doctrine, or advocacy towards positive social change from taking place within communities. This must be prevented at all costs. The SCT did uncover some truths surrounding these assumptions through evidence-based research. To a small degree, the evidence substantiates that compliance behavior during the COVID pandemic corresponded to different levels of importance toward positive behavioral changes in favor of enrolling in YouTube DPP, as assumed by Cannon et al. (2020), Nye (2020), and Ritchie (2020). Evidence indicate that the primary care clinician was still heavily relied on for enrollment into YouTube DPP (Ackermann et al., 2019). So, promoting viable solutions to positive social change in communities concerning DPP, would consist of providing the community with better insurance coverage options, strengthening doctor referral campaigns, and presenting information about cost, personal risk, and treatment options through smartphones (Ackermann et al., 2019; Holliday et al., 2019; Venkataramani et al., 2019). In addition, evidence from this study indicate that programs that focus on recipes that fit into diverse lifestyles and self-control would be most appropriate towards increasing enrollment into YouTube DPP nationwide. However, I recommend that future research should be done on different target populations to support my claim.

In short, the study approach and design were appropriate for validating the research question. The SCT was a good fit for this study, even though the health behavioral model could have been easily applied. In the future, more open-ended questions should be used to negate response bias and a larger sample size to elicit more data from the noncompliant and low compliant participant population. I also recommend using a more comprehensive list of enrollment questions to improve participant response scores relating to enrollment practices.

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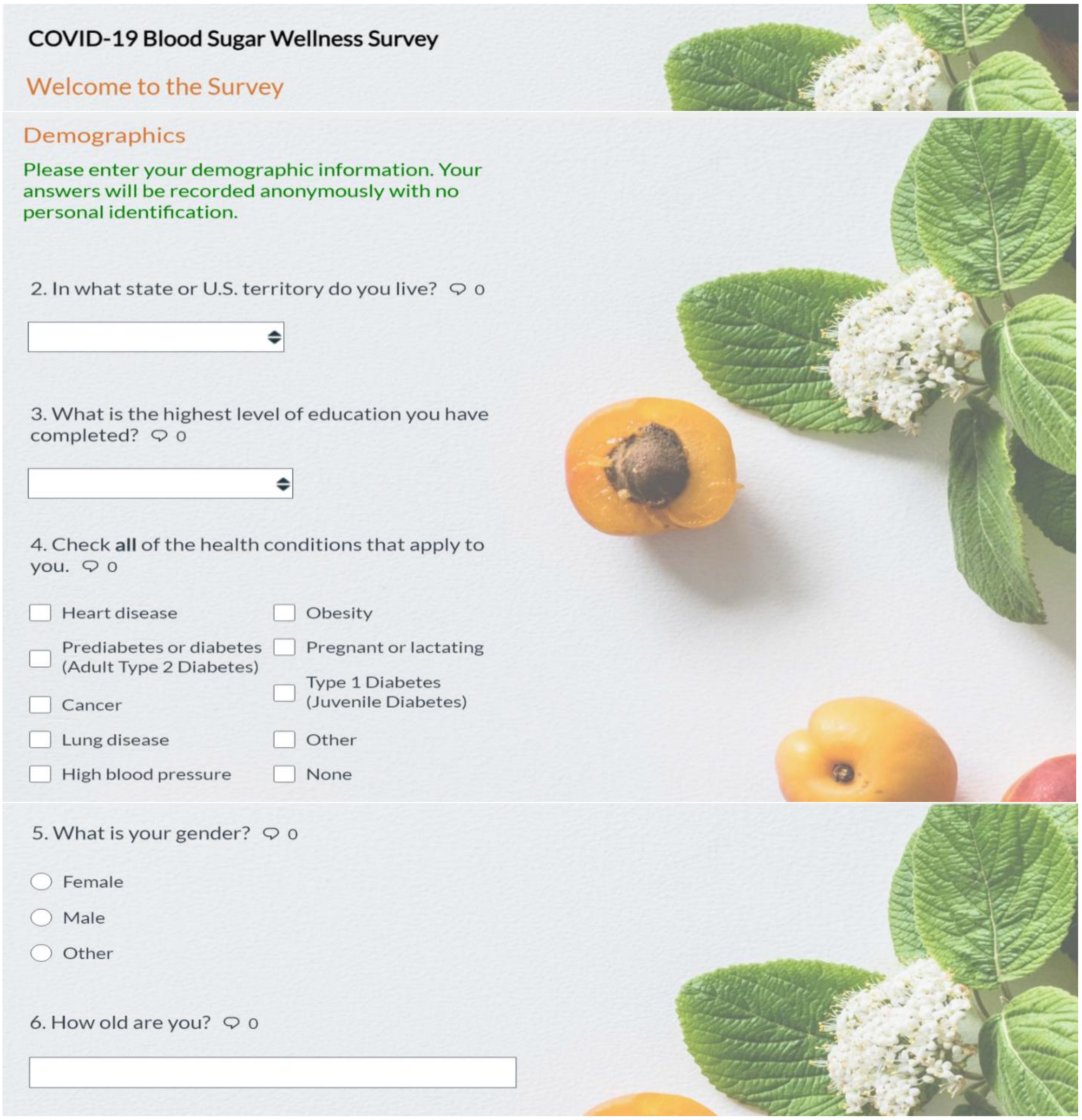
Appendix A: Survey Instrument



COVID-19 Blood Sugar Wellness Survey

Welcome to the Survey

Demographics

Please enter your demographic information. Your answers will be recorded anonymously with no personal identification.

2. In what state or U.S. territory do you live? 0

3. What is the highest level of education you have completed? 0

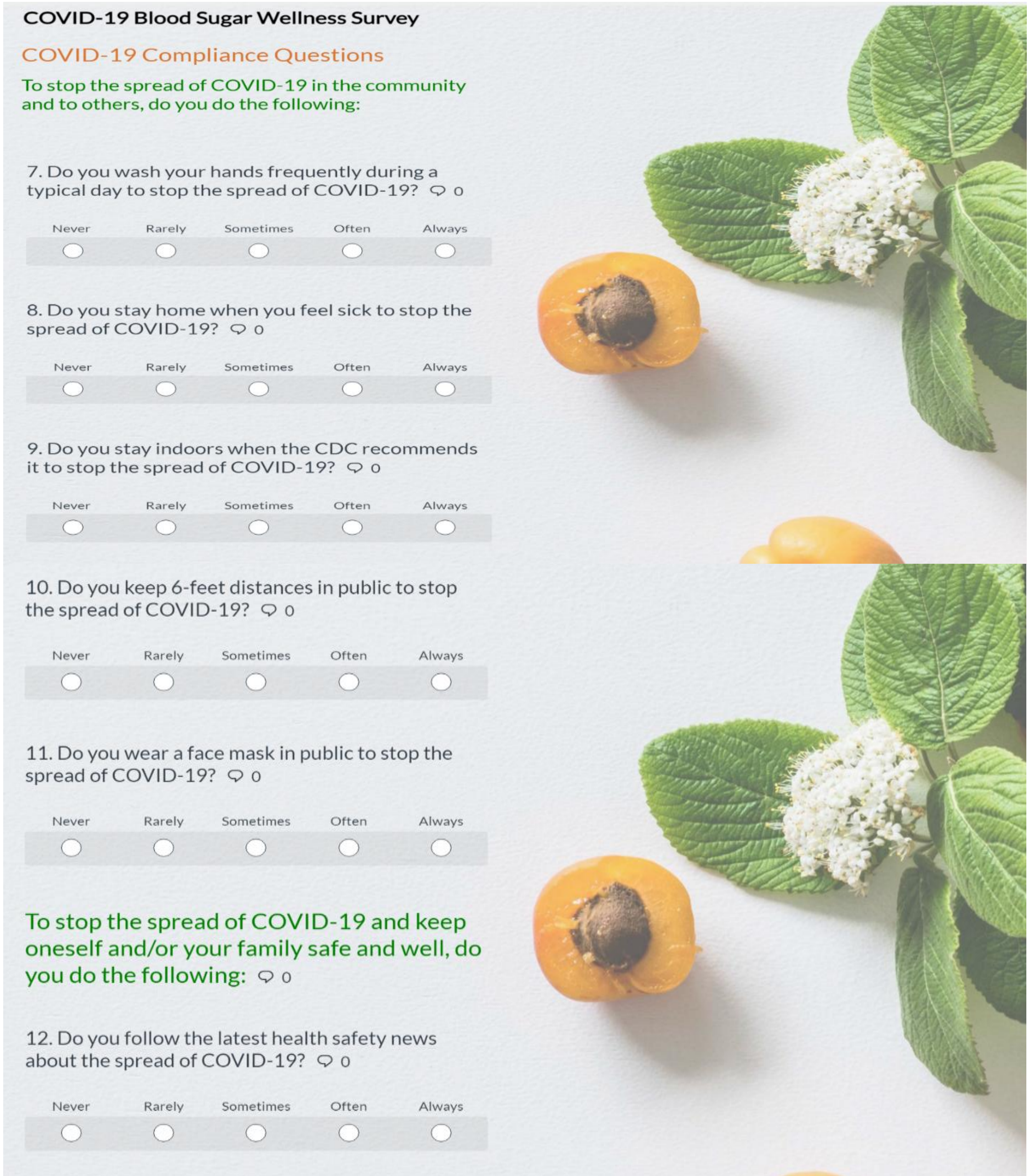
4. Check **all** of the health conditions that apply to you. 0

- ☐ Heart disease
- ☐ Prediabetes or diabetes (Adult Type 2 Diabetes)
- ☐ Cancer
- ☐ Lung disease
- ☐ High blood pressure
- ☐ Obesity
- ☐ Pregnant or lactating
- ☐ Type 1 Diabetes (Juvenile Diabetes)
- ☐ Other
- ☐ None

5. What is your gender? 0

- ◯ Female
- ◯ Male
- ◯ Other

6. How old are you? 0



COVID-19 Blood Sugar Wellness Survey

COVID-19 Compliance Questions

To stop the spread of COVID-19 in the community and to others, do you do the following:

7. Do you wash your hands frequently during a typical day to stop the spread of COVID-19? 0

Never	Rarely	Sometimes	Often	Always
○	○	○	○	○

8. Do you stay home when you feel sick to stop the spread of COVID-19? 0

Never	Rarely	Sometimes	Often	Always
○	○	○	○	○

9. Do you stay indoors when the CDC recommends it to stop the spread of COVID-19? 0

Never	Rarely	Sometimes	Often	Always
○	○	○	○	○

10. Do you keep 6-feet distances in public to stop the spread of COVID-19? 0

Never	Rarely	Sometimes	Often	Always
○	○	○	○	○

11. Do you wear a face mask in public to stop the spread of COVID-19? 0

Never	Rarely	Sometimes	Often	Always
○	○	○	○	○

To stop the spread of COVID-19 and keep oneself and/or your family safe and well, do you do the following: 0

12. Do you follow the latest health safety news about the spread of COVID-19? 0

Never	Rarely	Sometimes	Often	Always
○	○	○	○	○

13. Do you wash/wipe off groceries that you brought home from the store to stop the spread of COVID-19? 0

Never	Rarely	Sometimes	Often	Always
○	○	○	○	○

14. Do you cover your mouth when sneezing or coughing to stop the spread of COVID-19? 0

Never	Rarely	Sometimes	Often	Always
○	○	○	○	○

15. Do you cook your own meals to stop the spread of COVID-19? 0

Never	Rarely	Sometimes	Often	Always
○	○	○	○	○

16. Do you shower after going outside to stop the spread of COVID-19? 0

Never	Rarely	Sometimes	Often	Always
○	○	○	○	○

COVID-19 Blood Sugar Wellness Survey

Blood Sugar Questions

Select how important the following referral options are at convincing you to enroll in online YouTube diabetes prevention programs?

17. An online referral from a credible YouTube channel: 0

Not important	A little important	Important	Very important	Absolutely important
○	○	○	○	○

18. A virtual appointment referral from your primary doctor: 0

Not important	A little important	Important	Very important	Absolutely important
○	○	○	○	○

19. A face-to-face referral from a friend: 0

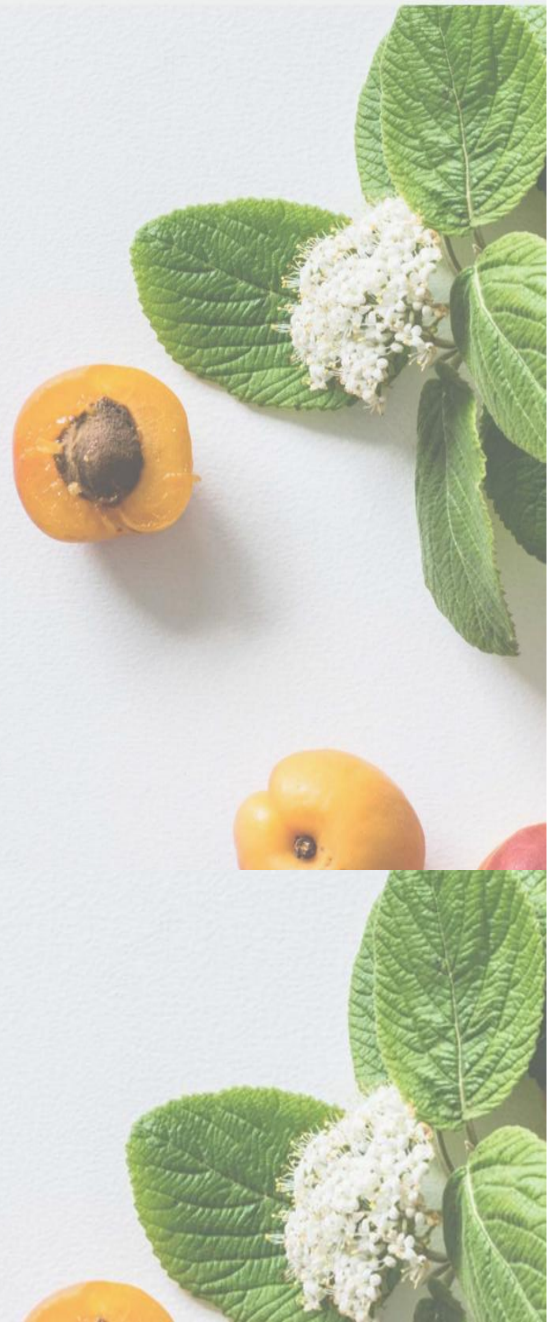
Not important	A little important	Important	Very Important	Absolutely important
○	○	○	○	○

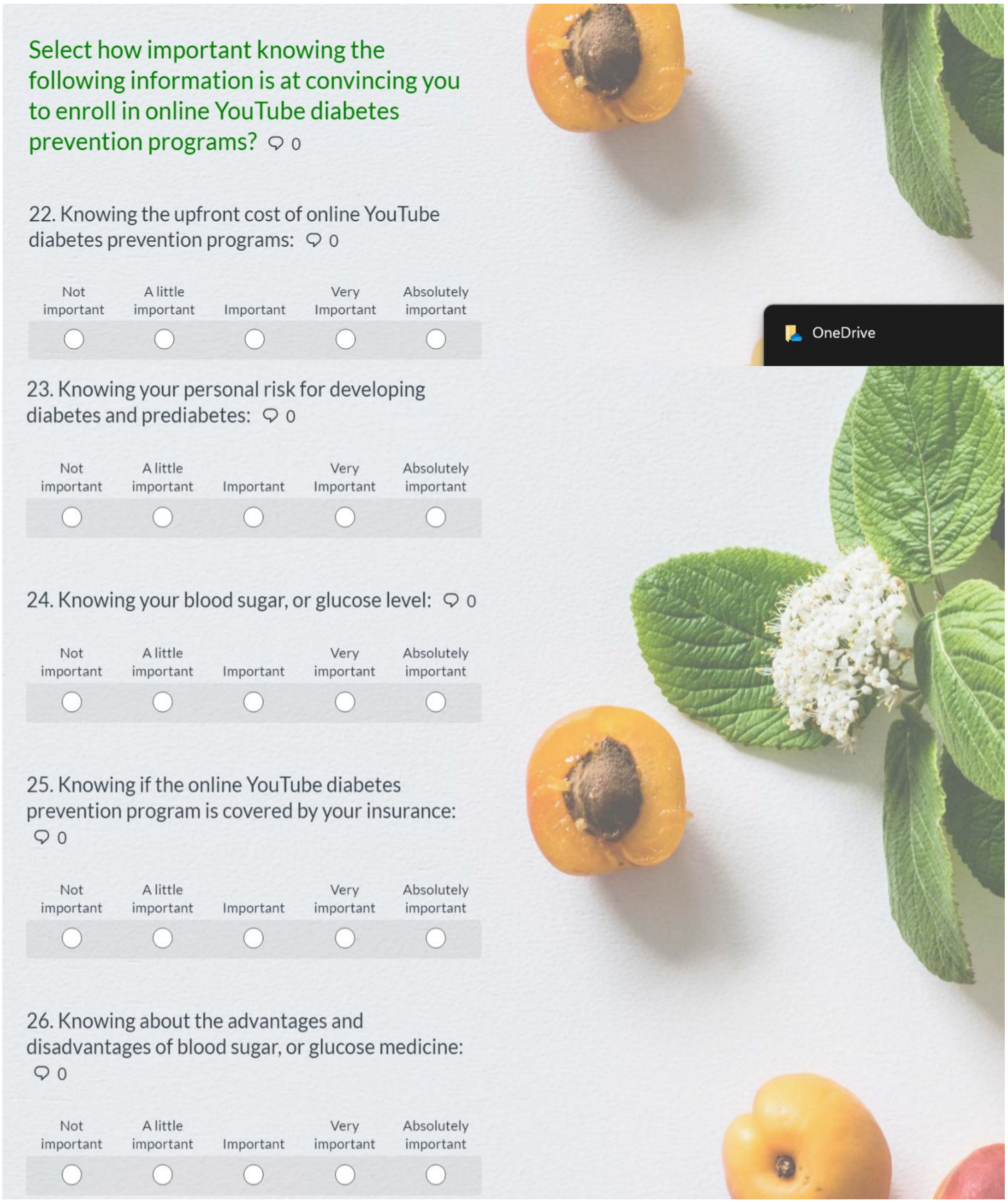
20. An online referral from a family member: 0

Not important	A little important	Important	Very Important	Absolutely important
○	○	○	○	○

21. A face-to-face referral from your primary doctor: 0

Not important	A little important	Important	Very Important	Absolutely important
○	○	○	○	○





Select how important knowing the following information is at convincing you to enroll in online YouTube diabetes prevention programs? 0

22. Knowing the upfront cost of online YouTube diabetes prevention programs: 0

Not important	A little important	Important	Very Important	Absolutely important
○	○	○	○	○

23. Knowing your personal risk for developing diabetes and prediabetes: 0

Not important	A little important	Important	Very Important	Absolutely important
○	○	○	○	○

24. Knowing your blood sugar, or glucose level: 0

Not important	A little important	Important	Very important	Absolutely important
○	○	○	○	○

25. Knowing if the online YouTube diabetes prevention program is covered by your insurance: 0

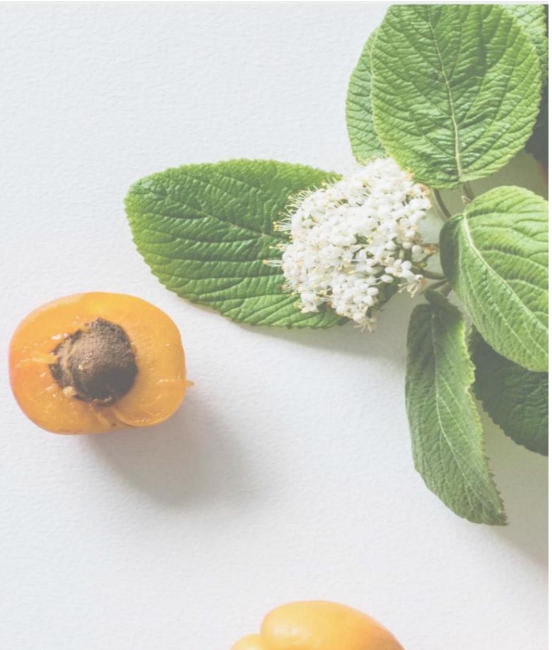
Not important	A little important	Important	Very important	Absolutely important
○	○	○	○	○

26. Knowing about the advantages and disadvantages of blood sugar, or glucose medicine: 0

Not important	A little important	Important	Very important	Absolutely important
○	○	○	○	○

OneDrive

Select how important the following YouTube diabetes prevention program commitments are at helping you maintaining your enrollment. 0



27. Committing 20 to 40 minutes for online sessions: 0

Not important	A little important	Important	Very important	Absolutely important
○	○	○	○	○

28. Being able to use smartphones or other devises to participate: 0

Not important	A little important	Important	Very important	Absolutely important
○	○	○	○	○

29. Being able to subscribe to online YouTube diabetes prevention program channels: 0

Not important	A little important	Important	Very important	Absolutely important
○	○	○	○	○

30. Getting frequent updates about online YouTube diabetes prevention programs: 0

Not important	A little important	Important	Very important	Absolutely important
○	○	○	○	○

31. Being able to buying what you saw on YouTube diabetes prevention programs: 0

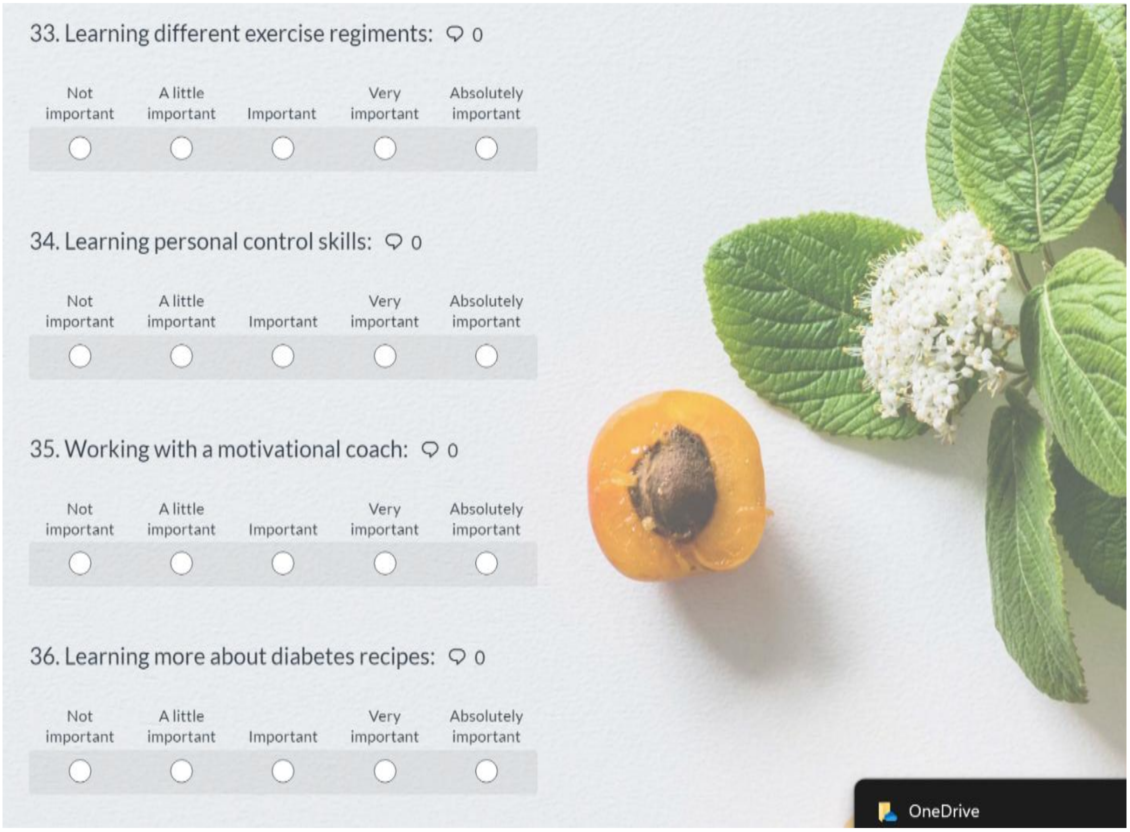
Not important	A little important	Important	Very important	Absolutely important
○	○	○	○	○

Select how important the following YouTube diabetes prevention program learning activities and skills are at helping you decide to enroll. 0

32. Learning groups: 0

Not important	A little important	Important	Very important	Absolutely important
○	○	○	○	○

OneDrive



33. Learning different exercise regiments: 0

Not important	A little important	Important	Very important	Absolutely important
○	○	○	○	○

34. Learning personal control skills: 0

Not important	A little important	Important	Very important	Absolutely important
○	○	○	○	○

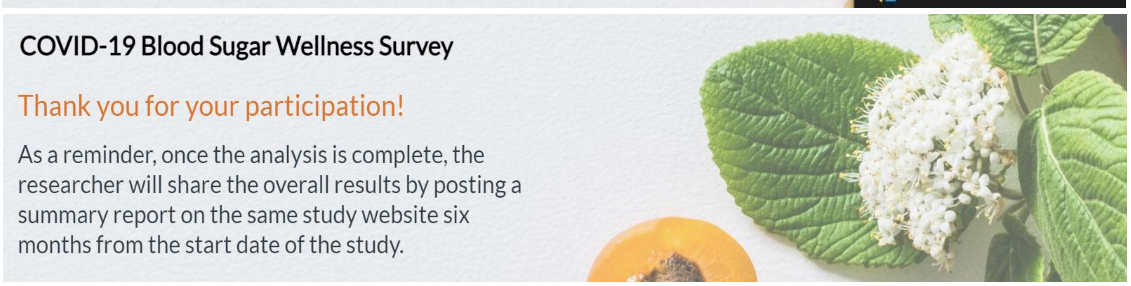
35. Working with a motivational coach: 0

Not important	A little important	Important	Very important	Absolutely important
○	○	○	○	○

36. Learning more about diabetes recipes: 0

Not important	A little important	Important	Very important	Absolutely important
○	○	○	○	○

OneDrive



COVID-19 Blood Sugar Wellness Survey

Thank you for your participation!

As a reminder, once the analysis is complete, the researcher will share the overall results by posting a summary report on the same study website six months from the start date of the study.

That's the end of the preview!

PREVIEW AGAIN COLLECT RESPONSES

Back to design

Appendix B: Flyer

Online survey study about enrolling in high blood sugar prevention programs seeks participants

There is a new study called *"The COVID-19 Blood Sugar Wellness Survey"* that could help doctors and health clinicians find better ways to understand and help their patients. For this study, you are invited to express your opinion about enrolling in high blood sugar prevention programs on YouTube during the COVID-19 pandemic.

This survey is part of the doctoral study for a Ph.D. student at Walden University. Approval #**from IRB number goes here**

About the study:

- This is a 5–10-minute online survey
- No names or contact information will be collected for your safety
- You can stop taking the survey at any time by closing the website

Volunteers must meet these requirements:

- 18 years old or older
- Currently live in the U.S.
- Active on social media, like Facebook or LinkedIn
- Not pregnant or lactating
- Have not been diagnosed with type 1 diabetes