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Relationship Between Social Media Screen Time, Sedentariness, and BMI Among Young Adults

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Abstract

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by

Helen Golod

MA, Capella University, 2014

BS, SUNY College at Old Westbury 2008

Dissertation Submitted in Partial Fulfillment

of the Requirements for the Degree of

Doctor of Philosophy

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Abstract

Obesity has quickly become an epidemic that affects adults and youth not only in the United States, but also increasingly elsewhere in the global community. Research suggests that most children and adolescents spend a significant amount of time indulging in screen-based leisure, especially on social media. Such behavior may also be linked to sedentary lifestyle, which can impact an individual's body mass index (BMI). To address this research problem, the purpose of this quantitative correlational study was to (a) examine the relationship between screen time on different types of social media (social networking sites, image-sharing sites, discussion sites, and video-hosting sites) and an individual's BMI and (b) determine how sedentariness moderates the relationship between screen time and BMI. Rosenstock's health belief model guided the study. English-fluent adults aged 18 to 25 years old living in the United States were the target population. A target sample size of 120 participants was selected from multiple states. The data collection process consisted of an online survey that included the Sedentary Behavior Questionnaire and additional questions about BMI, social media screen time, and participant demographics. The descriptive and multiple linear regression analyses were conducted at a 0.05 level of significance. The only significant finding was that ethnic groups significantly affected the amount of time associated with sedentary behavior. The findings from this research may inform positive social change through new insights about the health implications of time spent on social media for young adults, as well as lifestyle changes that could potentially lower rates of obesity and improve quality of life.

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Dedication

I dedicate this research to my family. My mom who stood by my side through good and bad times. My sister who always helped whenever I was struggling and never let me strive for anything less than my best. My grandma who always made sure I was fed and had what I needed. My dad who always supported me through the difficult years.

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Table of Contents

List of Tables

List of Figures

Chapter 1: Introduction to the Study

This study centered on the associations between device screen time on social media, body mass index (BMI), and sedentary behavior. In recent decades, young people's daily use of social media and other forms of electronic media has increased rapidly (Fuchs, 2017; Williams et al., 2019). Previous scholars have identified significant correlations between screen time, social media use, sedentary behavior, and health metrics such as BMI (e.g., Jackson & Cunningham, 2017; Mattoo et al., 2020); however, the implications of these associations are not well-understood, particularly among young adult populations. The current study may lend new insight to this topic, which could ultimately benefit the health and well-being of young adults and other young individuals whose daily routines include screen time and social media use.

In Chapter 1, I provide an overview of the current study. The chapter begins with the background of the study, followed by the problem statement. Subsequently, the purpose of the study is provided. The central research questions and hypotheses are listed thereafter, followed by the theoretical framework. The nature of the study is described, and key terms related to the study are defined. The assumptions, delimitations, scope, limitations, and potential significance of the study are then discussed. A summary concludes the chapter.

Background

Significant lifestyle changes have occurred in recent years following the emergence of new technologies and forms of media (Alley et al., 2017). Since 2001, sedentary behavior has increased significantly among individuals of all ages in the United

States (Yang et al., 2019). This increase in sedentary behavior has largely corresponded with the growth in daily consumption of electronic media and the rising popularity of social media (Greenwood et al., 2016). Americans, particularly young Americans, are spending increased amounts of their free time sedentary and/or using electronic devices (Melkevik et al., 2015). There is a lack of research regarding the health implications of these lifestyle changes, particularly among some young populations.

Recent scholars have shown excessive sedentary behavior and/or excessive social media use to significantly impact health, but these relationships are not well-understood. Melkevik et al. (2015) found that among adolescents who complied with national physical activity guidelines, electronic media use was a significant predictor of girls' BMI and likelihood of being overweight. Excessive or obsessive social media use can also adversely impact mental health; Bekalu et al. (2019) found that social media use was associated with negative physical and mental health outcomes among individuals who self-reported having an emotional connection to their social media use. The associations between social media use, sedentary behavior, and health are complex. Kranzler and Bleakley (2019) noted that while social media content can influence users to consider unhealthy lifestyle choices such as e-cigarette use, social media platforms may also host information about healthy diets and lifestyle choices that can positively influence users just as easily.

The multifaceted findings discussed in the preceding paragraph emphasize that a multitude of variables and contextual conditions can serve to determine the nature of associations between sedentary behavior, social media use/screen time, and BMI (Bekalu et al., 2019; Kranzler & Bleakley, 2019; Melkevik et al., 2015). Accordingly, research on these topics should be conducted in multiple contexts and among diverse populations to develop further clarity. Given the lack of research on this topic among young adults specifically, rather than adolescents (aged 10-17 years) or adults in general, the current research centered on young American adults (Dietz, 2017). The findings of this study may lead to new insights about how much time young adults should spend in front of screens, on social media particularly, as well as the lifestyle changes young adults can make to potentially lower obesity rates.

Problem Statement

The problem that I addressed through this study was a lack of understanding concerning how sedentary behavior moderates the relationship between screen time spent on different types of social media and BMI among young adults in the United States. Considering the 86% of Americans who have consistent Internet access, over 78% recently indicated their regular use of one or more social media platforms (Greenwood et al., 2016). Among multiple age groups, social media use and other forms of screen time have become an ever-present element of daily life (Alley et al., 2017; Fuchs, 2017; Melkevik et al., 2015). For the purposes of this study, screen time refers to the time individuals spend on social media through—but not limited to—websites and/or using electronic devices, including phones, televisions, and computers. Social media platforms are applications and websites that can be used for social networking (Fuchs, 2017). Popular social media platforms include Facebook, Twitter, Snapchat, Instagram, and TikTok, to name a few.

Excessive sedentariness, screen time, and/or social media use has been linked to detrimental health consequences in some contexts, including obesity (BMI > 30), being overweight (BMI > 25), depressive symptoms, and poor sleep (Chow, 2017; Jackson & Cunningham, 2017; Twenge, Joiner, et al., 2018). The findings from such studies, however, have varied considerably based on participant demographics and contextual factors (Bejarano et al., 2017; Biddle et al., 2017; Wachira et al., 2018). While numerous researchers have studied the relationships between screen time, sedentary behaviors, and health outcomes such as obesity (e.g., Bosch et al., 2019; Falbe et al., 2017; Wachira et al., 2018), there remains a lack of insight into these relationships among young adults specifically concerning social media screen time.

Purpose of the Study

The purpose of this quantitative correlational study was to examine (a) the relationship between screen time on different types of social media (social networking sites, image-sharing sites, discussion sites, and video-hosting sites) and an individual's BMI and (b) how sedentariness moderates the relationship between screen time and BMI. For the purposes of this, relevant screen time is any time spent actively using electronic devices to access different types of social media, regardless of whether users are multitasking or taking part in other activities simultaneously. A total of 135 young adults between 18 and 25 years old were selected from multiple U.S. states to participate in this study. The participants completed an online survey consisting of the Sedentary Behavior Questionnaire (SBQ) and additional questions about BMI, social media screen time, and participant demographics.

Research Questions and Hypotheses

The following research questions and corresponding hypotheses guided this study:

RQ1: Do relationships exist between screen time on the different types of social media (social networking sites, image-sharing sites, discussion sites, and video-hosting sites) and an individual's BMI?

$H_0$1: There is no significant relationship between screen time on the different types of social media and an individual's BMI.

H_a1: There is a significant relationship between screen time on the different types of social media and an individual's BMI.

RQ2**:** Does sedentariness moderate the relationship between screen time on the different types of social media and an individual's BMI?

$H_0$2: Sedentariness does not significantly moderate the relationship between screen time on the different types of social media and an individual's BMI.

H_a2: Sedentariness significantly moderates the relationship between screen time on the different types of social media and an individual's BMI.

Theoretical Framework

The theoretical framework for this study was Rosenstock's health belief model (HBM; 1974). The HBM describes how individuals' attitudes and beliefs about health may lead them to improve, change, or adapt their health behaviors (Rosenstock, 1974). While a desire to change one's diet, exercise, alcohol consumption, or drug use, adherence to medical treatment, and other lifestyle choices may be motivated or inspired by different factors, ultimately, changes to health behaviors commence when individuals' beliefs about health change in some way (Rosenstock, 1974). The reasons individuals' health beliefs change can be diverse, including—but not limited to—being advised by a healthcare professional, reading an article on the Internet, or experiencing sudden adverse health symptoms.

In the current study, the HBM model was used to frame the analysis of young adults' demographics, behaviors, and BMI. More specifically, I attempted to make connections and gain understanding about associations between social media use (screen time), time spent sedentary, and other behavioral factors that impact BMI in conjunction with attitudes and beliefs about these factors. Based on extant research findings and tenets of the HBM, I hypothesized that young adults with a high BMI may be likely to avoid in-person social contact and be more inclined to use social media more and enact sedentary behaviors to avoid some peers' judgments and bias based on their weight. The results of this research, however, may prove unpredictable based on the significant lack of HBM-based research on social media behaviors, particularly among young adults.

Nature of the Study

The quantitative methodology was employed for this study. Quantitative research centers on making statistical inferences about relationships between variables or the meaning of data that represents numerically measured variables (Camm, 2012). Because the aim of the study was to gather broad insights about associations between screen time on social media, BMI, and sedentary behavior among young adults, I focused on discerning statistically significant relationships among variables based on quantitative survey data. Using a qualitative approach, which instead centers on detail-rich data and analysis regarding the "how" or "why" of relationships between variables, could have potentially led to valuable insights regarding the central variables; however, the characteristics of qualitative research, such as smaller sample size and more complex data collection logistics, would have likely limited the transferability of the findings (Leavy, 2017).

A correlational research design was employed to address the central research questions. Correlational designs are employed to determine whether significant relationships exist between numerically measured variables (Curtis et al., 2016). I applied a correlational design to gather insights concerning how the moderating variable of sedentariness impacts the relationship between the predictor variable of screen time on different types of social media and the criterion variable of BMI.

The target population for this study included young adults aged 18 to 25 years old in the United States who are fluent in English. A random sampling strategy based on the broad criteria listed above was employed to identify and recruit participants from across the country. Random sampling entails identifying the pool of all potential volunteers for the study, all of which have an equal probability of being chosen, and subsequently selecting the desired sample size from this pool (Creswell, 2012). A multiple linear regression analysis accounting for eight predictors (four predictors and four interaction variables), an 80% power test, an .05 level of significance, and a medium effect size (f^2 = .20) led to the determination that the minimum sample size or this study was 120. Considering the number of young adults in the United States, as well as the possibility of participant withdrawals or participants with missing/incomplete responses, I aimed to select a total of 135 young adults.

Potential participants were contacted on popular social media platforms such as Facebook, Instagram, and Twitter. The qualified participants completed the SBQ of Rosenberg et al. (2010), in addition to a self-developed questionnaire centering on BMI, social media screen time, and demographic questions. The selected research instruments were administered through an online survey. Statistical Package for the Social Sciences (SPSS) for Windows software was used to organize and analyze the collected data. Descriptive analysis, multiple linear regression analysis, and hypothesis testing was conducted for both research questions using a 0.05 level of significance (see Weakliem, 2016).

Definitions

The following key terms and definitions are provided to clarify concepts that are central to the current study:

Body mass index (BMI): Body mass index is a metric used to estimate body fat based on an individual's height and weight (Jackson & Cunningham, 2017). Generally, a BMI below 18 is considered underweight, a BMI from 18-25 is considered normal, a BMI above 25 is considered overweight, and a BMI above 30 is considered obese.

Screen time: Screen time is time individuals spend consuming electronic media and/or using electronic devices, including phones, televisions, and computers (Christensen et al., 2016). For the purposes of this study, screen time refers to time spent actively using electronic devices, regardless of whether users are multitasking or doing other activities at the same time.

Sedentary behavior: Sedentary behaviors occur while an individual is awake and expending 1.5 or fewer metabolic equivalents (METs); this usually occurs when an individual is lying down or sitting (Fukai et al., 2016; González et al., 2017; Tremblay et al., 2017). The MET is the objective measure of the ratio of the rate at which a person expends energy, relative to the mass of that person, while performing some specific physical activity compared to a reference, set by convention at 3.5 mL of oxygen per kilogram per minute, which is roughly equivalent to the energy expended when sitting quietly (Tremblay et al., 2017).

Social media: Social media platforms are applications and websites that can be used for social networking (Fuchs, 2017). Popular social media platforms include Facebook, Twitter, Snapchat, Instagram, and TikTok.

Assumptions

Several assumptions underpinned the current study. Due to the self-reported nature of the data, I assumed that participants would answer the survey questions honestly and to the best of their ability. Participants did not receive any incentives to participate, and they were reminded that their data would not reflect their name or any other identifying information after the analysis was undertaken. I also assumed that the data would represent young adults living in urban and suburban areas of the United States more than the experiences of individuals living in rural communities, given the topic of the study and the irregular Internet access or connectivity issues experienced in many rural regions of the country. Lastly, based on the principles of the HBM, I assumed that participants' personal beliefs about their health and/or their beliefs about 'healthy' amounts of screen time, social media use, and sedentary behavior impact their participation in these behaviors.

Scope and Delimitations

The scope of this study entailed only discerning the relationships between variables; thus, I did not assume that causation could be determined for any relationships between variables. The central variables for this study were screen time on social media platforms, BMI, and sedentary behavior. The research participants were delimited to young adults between 18 and 25 years old due to the lack of relevant research conducted among this population and the relative popularity of social media among young adults. Participants were also delimited to individuals who are fluent in English to prevent potential translation issues or research effects. Participants representing all health beliefs, BMIs, social media activity levels, and levels of sedentary behavior were admitted to the study to ensure that the results reflect a broad population of young U.S. adults.

Limitations

Specific limitations are also associated with this research as well. Due to the self-reported nature of the data, it is possible that some participants' responses were not honest or did not accurately reflect their reality. Participants were assured that their answers would remain anonymous to discourage inaccuracies. Another potential limitation was that participants from regions of the United States with poor or inconsistent Internet access may have been underrepresented, as it stands to reason that young adults who have trouble accessing the Internet regularly are less likely to use social media and would be unlikely to indicate interest in a study on social media use. Additionally, because participants were selected solely from the United States, another limitation was that a global perspective may not be reflected in the results of the study. A screening section of the online survey was implemented before the main survey questions, and a demographic portion of the survey lent insight into what state/region participants live in.

Significance

The results of this research may inform new understandings of how much time young adults can spend in front of screens, and on social media in particular, before these habits become detrimental to their health. Many studies aimed at exploring associations between social media use and health have either centered on adolescent (10–17 years) or adult (18+ years) populations, with little distinction between adolescent, adult, and young adult trends and patterns (Dietz, 2017). The findings of this study may also lend insight into what lifestyle changes young adults can make that could lead to lower obesity rates or improved quality of life, as well as the influence of sedentariness as a moderating variable.

This study also represents a novel application of the HBM. The HBM has been used previously to examine social media use and behavior; however, such applications have largely centered on the use of social media as a health information source, rather than the health implications of social media use itself (e.g., Kite et al., 2018; Zhang et al., 2017). In the current study, the HBM was used to frame insights about associations between social media use, sedentary behavior, and BMI, and how health beliefs may influence these associations.

Summary

Through this study, I addressed the lack of understanding concerning how sedentary behavior moderates the relationship between screen time spent on different types of social media and BMI among young adults in the United States. The purpose of this quantitative correlational study was to (a) examine the relationship between screen time on different types of social media (social networking sites, image-sharing sites, discussion sites, and video-hosting sites) and an individual's BMI and (b) determine how sedentariness moderates the relationship between screen time and BMI. The theoretical framework for this study was Rosenstock's (1974) HBM, which describes how individuals' attitudes and beliefs about health may influence them to change certain health behaviors. A sample of 135 young adult participants between 18 and 25 years old was selected from multiple U.S. states. The participants completed an online survey, the results of which were analyzed using descriptive analysis, multiple linear regression analysis, and hypothesis testing at an 0.05 level of significance (see Weakliem, 2016). Chapter 2 consists of a literature review pertaining to the central variables of the study.

Chapter 2: Literature Review

The problem that I addressed through this study was how sedentary behaviors moderate the relationship between screen time spent on different types of social media and BMI among young adults in the United States. While previous investigators have studied screen time and sedentary behaviors in relation to health and obesity (e.g., Bosch et al., 2019; Falbe et al., 2017; Wachira et al., 2018), there remains a lack of insight into these relationships among young adults where social media screen time, specifically, is concerned. The purpose of this quantitative correlational study was to (a) examine the relationship between screen time of different types of social media such as social networking sites, image-sharing sites, discussion sites, and video-hosting sites and an individual's BMI and (b) determine how sedentariness moderates the relationship between screen time and BMI. The results of this research may inform new understandings of how much time should be spent in front of screens, on social media in particular, and what lifestyle changes young adults should make to lower obesity rates. Within the context of this study, young adults and adolescents were distinguished; the focus of this research was young adults, who are typically referred to as being 18 to 25 years old, and not adolescents, who are typically referred to as being 10 to 17 years old (Dietz, 2017).

This chapter consists of a review of relevant literature. To locate articles for this review, EBSCOhost and Google Scholar research databases were used. The following key terms and phrases were used as search terms to locate relevant research: *sedentary behavior* (30), *screen time* (38), *social media* (8), *sedentary behavior and BMI* (6), *screen* *time and BMI* (10), and *obesity prevention* (16). While some seminal and older theoretical works are included to inform the historic basis of the study, most sources discussed in this chapter were written within the past 5 years to ensure their continued relevance.

The chapter begins with a discussion of the theoretical framework within the context of the current study. Subsequently, screen time and social media use are discussed. Sedentary behavior is discussed thereafter, followed by obesity prevention among young adults. All three of these topics are discussed in association with health and health behaviors in corresponding subsections. A summary concludes the chapter.

Theoretical Framework

The theoretical framework for this study is Rosenstock's (1974) HBM. The HBM represents the notion that as the result of an individuals' attitudes and beliefs, people may improve, change, or adapt their health behaviors (Rosenstock, 1974). This model speaks to the factors which impact diet, exercise, alcohol or drug use, adherence to medical treatment, and other lifestyle choices which affect health. Individuals may feel motivated or inspired to change health behaviors for many reasons, ultimately, changes to health behaviors occur when individuals' beliefs about health in general, their own health, the health of others, or the notion of healthy living change for one reason or another. It is also important to note that while the HBM is usually referenced within the context of pursuing positive health changes, it can also explain how individuals adopt unhealthy behaviors and lifestyle changes (Khoramabadi et al., 2016). For instance, if an individual does not see or feel physical changes as quickly as they anticipated after adopting a healthier diet, their beliefs may shift from thinking that eating healthier is worthwhile to thinking they will look and feel the same regardless of dietary changes.

The HBM has informed approaches to addressing numerous public health crises and challenges including obesity in childhood and young adulthood, as well as the negative implications of excessive sedentary behavior. Puhl and Latner (2007) explained that “overweight adolescents are more likely than non-overweight youths to engage in disordered eating behaviors such as binge eating and chronic dieting” (p. 568); these unfavorable diet-related health behaviors are often tied to health beliefs and behaviors associated with physical activity. Individuals with sedentary lifestyle tend to engage in non-physical activity including media consumption more frequently (Melkevik et al., 2015). Further, Puhl and Brownell (2003) explained that many children and young adults strengthen the stigma associated with being overweight and/or obese by ostracizing peers based on their weight: "If a person believes that obese people are responsible for their fatness, s/he will blame and stigmatize them” (p. 216). Being treated in this way can then lead overweight children and young adults to withdraw socially or spend more time sedentary and behind screens, further reinforcing unfavorable health behaviors.

Some research with a theoretical foundation that is grounded in the HBM has involved a focus on social media. In most studies of this nature, the authors solely focused on the influence of social media as a source of information. Kite et al. (2018) and Zhang et al. (2017) investigated social media as a platform which serves as a site of social discourse about health and a source of health information that can impact health beliefs. Indirect associations between childhood obesity and health information viewed by mothers on social media were also explored by Doub et al. (2016). While such studies have revealed significant associations between health information sourced from social media sites and health behaviors, they often ignore the influence of the unique, interactive nature of social media. The impacts of not only viewing health information, but also viewing and/or participating in discussions about health, as well as other features which distinguish social media information from information in online articles and other static sources, are not well understood.

To conduct this study, a quantitative correlational methodology was used to examine the relationship between screen time on different types of social media and an individual's BMI and how sedentariness moderates the relationship between screen time and BMI. Based on extant research findings and tenets of the HBM, I hypothesized that many young adolescents with high BMI avoid socializing in person and opt for frequent social media use and sedentary behaviors due to concerns about their peers' perceptions and bias based on their weight. Due to the significant lack of HBM-based research on social media as anything more than a source of health information, the results of this study may prove unpredictable.

Review of the Literature

Screen Time and Social Media Use

This section addresses the concepts of screen time and social media use. The definition of screen time and recent trends are identified. Social media use patterns and trends in recent years are identified, with a particular focus on how young people use social media. Subsections provide a discussion of the health implications of screen time, the association between screen time and BMI, and an overview of the health implications of frequent social media use.

Screen Time

Screen time describes time individuals spend using electronic devices, including phones, televisions, and computers. Some confusion exists, however, due to disagreement on the nature of screen time in existing literature (Madigan et al., 2019; Suggate & Martzog, 2020). Some researchers describe screen time as periods of the day when electronic media is consumed, while others consider it as when electronic devices are in use (Christensen et al., 2016). Some questions that have been raised on research related to screen time include: Does screen time entail the continuous use of electronics for an extended period? Should researchers distinguish between ‘passive’ screen time, like watching TV on the couch, and active screen time, such as when someone plays with a Wii or other gaming consoles which involve physical activity? (Downing et al., 2017). Does the notion of “screen time” assume the viewer is sedentary? (Kim et al., 2020). Thus, seeing the term “screen time” used in two different studies may refer to related—but slightly different—concepts. In the context of the current study, screen time refers to any time spent actively using electronic devices, regardless of whether users are multitasking at the time.

Like sedentary behavior, screen time has been on the rise in recent years in most industrialized nations among young people. Numerous new forms of communication technology, including social media and smartwatches, have emerged in the last 2 decades (Bucksch et al., 2016; Joshi et al., 2016; Larson et al., 2019; Venetsanou et al., 2019);

further, owning technologies such as cell phones and computers, which once signaled privilege and wealth, is now the norm. Many technologies used for screen time are not seen as extraneous anymore, or reserved for leisure time; rather, screen time is fused into everyday life (Adams et al., 2018; Bucksch et al., 2016; de Zepetnek et al., 2017; Domingues-Montanari, 2017). Trends in screen time, namely prolonged screen-time behaviors (STBs) were investigated by Bucksch et al. (2016) across 30 countries. Their data were sourced from the Health Behavior in School-Aged Children cross-national survey. Their results revealed that while TV viewership marginally decreased among male and female children between 2002 and 2010, overall screen time increased significantly during this period due to significantly increased time spent on computers. Further, STBs were more common among boys than girls and were more likely to occur during the weekend when children had more free time. These Bucksh et al.'s findings indicate that screen time, overall, is on the rise among global youth.

Aside from standardizing a definition for screen time, developing reliable and valid measures for evaluating screen time is key for research purposes. A questionnaire to assess screen time among adult participants was recently developed and evaluated by Vizcaino et al. (2019). An 18-item survey was produced which quantifies screen time while using smartphones, TV, and other commonly used devices. All but one item on the questionnaire, which pertained to smartphone use on the weekend, were found to be reliable and valid questions. Vizcaino et al. noted the need for more objective measures of screen time that are not based on individuals' subjective definitions of high versus low levels of screen time. This research's weakness parallels the lack of a standardized definition for screen time (Suggate & Martzog, 2020).

Numerous researchers have studied screen time in relation to health. In many cases, research on the relationship between screen time and health demonstrates a similar focus as research on the relationship between sedentary behavior and health (Robertson et al., 2018; Wang et al., 2019); many researchers have aimed to determine how increased or decreased screen time impact parameters of health such as depressive symptoms and BMI to determine whether excessive screen time has a detrimental impact (Parent et al., 2016; Saunders & Vallance, 2017). The following subsections detail the identified associations between screen time and health and screen time and BMI, respectively.

Screen Time and Health

While associations between screen time and health are often compared to associations between sedentary behavior and health, the implications can vary considerably. Some individuals avoid screen time almost entirely but may spend a considerable amount of time sedentary during the day due to attending school or working at a desk (Chow, 2017; Mielke et al., 2017; Wachira et al., 2018). Further, screen time is often assessed as a leisure activity (Garcia et al., 2017; Tanaka et al., 2017); thus, screen time which is required for school or work may be ignored.

Numerous researchers have recently sought to examine associations between screen time and psychological changes over time, particularly among children. Some researchers have tied increased screen time in the past decade to negative changes to sleep patterns (Ghekiere et al., 2019), depressive symptoms, and other facets of psychological well-being among children (Twenge, Martin, et al., 2018). The relationships between screen time and psychological well-being, in addition to potential mediating variables, are still not well understood and require further research.

Like sedentary behavior, many researchers have studied screen time in relation to health behaviors. In particular, the implications of screen time and exercise have been examined (Chow, 2017; Serrano-Sanchez et al., 2011). The results from a questionnaire administered to 262 young adults revealed that participants who spent 5 or more hours a day on screen time had higher BMIs, but only if they exercised for less than 5 hours a week. Further, "there was no relation between screen time and BMI among people who spent more than 4 h of exercise a week" and "between exercise groups who spent less than 5 h of screen time a day, there was no relation between hours of exercise and BMI" (Chow, 2017, p. 24). Chow's (2017) results suggest that exercise has a mediating influence on how screen time impacts certain health metrics. In a similar study, Serrano-Sanchez et al. (2011) researched the relationship between physical activity and screen time among a sample of 3,503 Spanish adolescents, reporting that approximately 26% of boys and 46% of girls did not meet national health recommendations for moderate to vigorous physical activity (MVPA) for their age group. There was not a strong association between screen time and physical activity among female participants; however, boys who took part in 4 hours per week or more of screen-time showed a 64% increased risk of not achieving the recommended weekly amount of MVPA for adolescents. The results of these studies highlight the associations between exercise and screen time among young people.

Screen Time and BMI

Perhaps the most common health metric that has been studied in relation to screen time is BMI. While many researchers have found significant associations between BMI and screen time, there remains a lack of consensus (Cai et al., 2017; De Decker et al., 2016; Jackson & Cunningham, 2017). This lack of consensus may be due, in part, to differences in terms of how screen time is conceptualized and measured. Bickham et al. (2013) investigated young adolescents' screen media use involving television, computers, and video games. The results of their analysis revealed that a higher proportion of participants' attention to watching TV was positively associated with higher BMI. Time spent watching television, however, was not directly related to BMI. Neither duration of use nor attention paid to video games or computers was associated with BMI. The results of this research raise further questions about why the use of different forms of media were not associated with BMI in the same way. Falbe et al. (2017) also distinguished between different forms of screen time in a study on associations between screen time and BMI. The researchers conducted a study to assess relationships between new forms of television (TV) viewing—recorded, online, downloaded, and on hand-held devices—and active video games with BMI. The authors reported that among women, online TV, TV viewed on hand□held devices, and the sum of nonbroadcast TV viewing time were associated with higher BMI. Broadcast TV viewing was also associated with higher BMI in women and men.

Many researchers, including Bickham et al. (2013) and Falbe et al. (2017), have found some degree of association between screen time and BMI. Other researchers, however, have evidenced no such relationship. Wachira et al. (2018) conducted a study regarding the relationship between screen-based sedentary behavior and childhood obesity. Their results showed that screen time was not associated with percent body fat, excluding weekend days where participants classified as obese had higher screen time. Moreover, screen time was not associated with BMI. These findings demonstrate conflicting results regarding the relationship between screen time and BMI.

Most research on the association between BMI and screen time has been conducted among populations of young individuals, from children to young adults. There is evidence indicating that the association between screen time and BMI differs significantly between youth and adults, but the lack of consensus among researchers makes those distinct differences unclear (Bejarano et al., 2017; Biddle et al., 2017). Despite the lack of consensus, Biddle et al. (2017) contended that associations between BMI and screen time have been proven more consistently among samples of children than adults, and associations between BMI and screen time have been proven more consistently than associations between BMI and sedentary behavior.

Social Media Use

This section centers on social media and how it is used. Social media use patterns and trends in recent years are identified, with a particular focus on how young people use social media. A subsection provides an overview of the health implications associated with frequent social media use.

Social media describes applications, websites, and platforms that are used for social networking. Social media use has exploded across the globe in the past decade

(Fuchs, 2017; Greenwood et al., 2016). A recent study conducted by the PEW Research Center found that of the 86% of Americans who have regular access to the Internet, 79% use Facebook, 32% use Instagram, 31% use Pinterest, 29% use LinkedIn, and 24% use Twitter (Greenwood et al., 2016). Social media is integrated into the daily lives of more people than it is not; for future generations, the idea of not using social media or social media not being integrated into many aspects of daily life could be unthinkable.

Regular or frequent social media use as a social norm has slowly begun to shift facets of many individuals' lifestyles and habits. Individuals make choices about the way they want to spend the finite amount of time available to them each day; thus, adopting the habit of checking or posting to social media daily functions to shift time away from other activities that might have occurred if social media use was not an option (Alley et al., 2017). Alley et al. (2017) investigated the impact of increasing social media use on sitting time among 1,140 participants who took part in the 2013 Queensland Social Survey. The results of the generalized linear models revealed that participants with a high social media use score had significantly greater total sitting times while using a computer in leisure time and significantly greater total sitting time on non-workdays. The results of this study suggested that high levels of social media use led to more time sitting, which may have otherwise been spent doing nonsedentary activities.

It is important to note that use of these platforms is not consistent across age groups. For example, LinkedIn is almost exclusively used by adults and some young adults, while Facebook is used by a wide range of users, from adolescents through seniors (Greenwood et al., 2016). Frequency of use also varies across social media platforms.

Approximately 76% of Facebook users use the platform daily, compared to 51% of Instagram users, 42% of Twitter users, 25% of Pinterest users, and 18% of LinkedIn users (Greenwood et al., 2016). These findings suggest significant variance among social media users, and that social media users should not be treated as a monolith within the context of research on social media use. A social media user who checks their feed and posts multiple times a day is likely to have significantly different perspectives, cognitive processes, and motivations than one who only checks a single social media profile once per week.

Many have touted social media as a significant development that has brought innovation to numerous industries, marketing practices, and interpersonal relationships (Greenwood et al., 2016). Social media has expanded possibilities, making it easier for individuals to connect with others located all around the world, and to find brands, products, information, and entertainment that interests them (Greenwood et al., 2016). Not all researchers and experts view the impact of social media as beneficial, however. Concerns of data privacy, shady marketing tactics, catfishing, and "fake news" abound given the current set of regulations (Greenwood et al., 2016). Further, some research evidence has indicated associations between health and social media use which are unfavorable (Greenwood et al., 2016). The following subsection offers more insight into relationships between social media and certain aspects of health.

Social Media Use and Health

The global popularity of social media has led numerous researchers to examine how social media use affects health. Researchers and health experts alike are particularly concerned about the impact of social media on young people whose brains are still developing and are more easily influenced than adults (Bekalu et al., 2019). Key areas of health-related social media research include mental health and well-being, obesity, and physical activity.

The lifestyle changes and habits associated with adopting frequent social media use may be detrimental to physical health. Melkevik et al. (2015) conducted a cross-national survey of teenagers from 30 different countries, finding that electronic media use was associated with increased BMI and odds of being overweight among both boys and girls who did not comply with physical activity guidelines. Among adolescents who complied with weekly physical activity recommendations, electronic media use was also found to be significantly associated with BMI and odds of being overweight among girls, but not among boys. The results of this research suggest that use of social media platforms specifically may not contribute to obesity among young people, but rather increased use of electronic media in general as a result of social media use (Melkevik et al., 2015).

Recent researchers have indicated that social media use impacts mental health outcomes differently depending on how individuals perceive and interact with social media. An individual can use social media daily for multiple hours each day, but only perceive it as a source of passive entertainment (Alonzo et al., 2019; Kranzler & Bleakley, 2019); conversely, an individual can only use social media once per week, but perceive it as a source of approval and self-esteem. Bekalu et al. (2019) recently surveyed 1,027 American adults to examine health outcomes in relation to social media use and perceptions of social media. Analysis of the data revealed that regular use of social media was significantly related to positive health outcomes. Having an emotional connection to regular social media use was significantly related to negative health outcomes. The strength of these relationships varied depending on respondents' racial/ethnic and socioeconomic subgroups (Bekalu et al., 2019). These findings suggest that researchers should consider the health implications of social media use from a more holistic perspective, rather than a dose-effect approach.

Like Bekalu et al. (2019), Kranzler and Bleakley (2019) emphasized the need for a holistic approach to researching how social media impacts certain health outcomes. Ample research evidence supports the notion that social media can influence the behavior of young people; however, researchers tend to focus on the possible negative health implications of social media as a problem to be addressed, without a clear understanding of why social media may impact health in the first place. Kranzler and Bleakley offered the example of substance abuse among young adults to illustrate potential health implications:

> Indeed, exposure to pro-substance use content via social media has been associated with a greater likelihood of substance use. A recent meta-analysis demonstrated positive associations between alcohol-related social media engagement and self-reported drinking and alcohol problems among adolescents and young adults. Celebrity endorsement of e-cigarette brands has been shown to significantly increase positive attitudes toward e-cigarettes and smoking

> intentions, and social media e-cigarette exposure was associated with current e-cigarette use and positive outcome expectancies. (2019, p. 141)

Despite their findings which support the notion that young adults are highly vulnerable to adopt negative health behaviors as a result of social media use, Kranzler and Bleakley (2019) were also quick to note that social media can just as easily lead young adults to make healthy and positive changes. These researchers highlighted previous research evidence that social media platforms can be leveraged as agents for favorable behavior change. Specifically, social media–based behavioral interventions have been found to be associated with improved nutrition behaviors including increased fruit and vegetable intake, decreased consumption of sugar-sweetened beverages, and reduced smoking and cessation outcomes (Kranzler & Bleakley, 2019). The researchers concluded by noting that social media can be a powerful tool for health-related change among young adults; whether changes are to the benefit or the detriment of one's health is contextual. Like Bekalu et al. (2019), Kranzler and Bleakley (2019) also concluded by noting that whether—or how—regular social media use impacts health outcomes is often dependent on how an individual perceives and uses social media.

Patterns of social media use have also been studied in relation to mental health outcomes with the ultimate goal of generating insight about why such relationships exist. Survey data from 1,730 American adults between the ages of 19 and 32 were collected and analyzed by Shensa et al. (2018) using logistic regression methods to examine associations between social media use patterns and self-reported depression and anxiety. Five clusters described the participants' social media use patterns: "'Wired', 'Connected', 'Diffuse Dabblers', 'Concentrated Dabblers', and 'Unplugged'" (p. 117). The two clusters which were characterized by the most frequent and consistent use of social media ("Wired" and "Connected") were significantly more likely to experience anxiety and depression than respondents in the other clusters. Shensa et al. concluded by noting a need to address problematic social media usage patterns, rather than time spent on social media.

Used as a tool and a resource, social media has been involved in some interventions aimed at improving health and wellness (Gabarron et al., 2018). For some conditions and health concerns, providing patients with access to patient education so that they make more informed health decisions is one of the most difficult aspects of care. Thus, Gabarron et al. (2018) reviewed "current existing evidence on the use of social media in interventions targeting people affected with diabetes" (p. 38) to better understand how effectively social media can be used as a health intervention and patient education tool. A review of four research databases and 20 highly relevant studies revealed a lack of evidence pertaining to diabetes interventions involving social media. These authors presented significant evidence of social media being used to improve patient outreach, education, and access to interventions used to address other health conditions (Gabarron et al., 2018). Their findings suggest that social media can improve health intervention effectiveness in some cases when used appropriately.

Sedentary Behavior

This section centers on the definition and nature of sedentary behavior. Recent trends in sedentary behavior are also identified. A subsection includes a discussion of the health implications of sedentary behavior.

The metabolic equivalent of task (MET) is the objective measure of the ratio of the rate at which a person expends energy, relative to the mass of that person, while performing some specific physical activity compared to a reference, set by convention at 3.5 mL of oxygen per kilogram per minute, which is roughly equivalent to the energy expended when sitting quietly (Tremblay et al., 2017). Sedentary behavior describes behavior while someone is awake that expends a low amount of energy (Fukai et al., 2016; González et al., 2017); specifically, an expenditure of 1.5 or fewer metabolic equivalents (METs), which usually occurs when someone is lying down or sitting (Tremblay et al., 2017).

While the definition of sedentary behavior is relatively straightforward, Tremblay et al. noted inconsistencies with how sedentary behavior is measured in research studies. Some researchers have assessed bouts, or extended periods of sedentary behavior, while others measure the number of times sedentary behaviors occur, the average length of sedentary bouts, or average METs throughout the day (Holtermann et al., 2017). Further, some researchers, including Saint-Maurice et al. (2016), have contended that definitions and assessments for sedentary behavior should be different for children and adults.

The lifestyle an individual leads directly determines the amount of sedentary behavior that occurs daily (Kehler et al., 2018; Peterson et al., 2018). For instance, a healthy adult with a full-time job working at a desk will almost always spend more time performing sedentary behaviors than a four-year-old child, as young children are rarely bound to routines that require the same extended periods of sedentary behavior for hours every day (Diaz et al., 2016). Peterson et al. (2018) cautioned, however, against assuming that young people are inherently more active and nonsedentary and that older adults are inherently sedentary and less active. In a recent study of sedentary behavior, physical activity, and BMI among college students (n = 48 males and n = 46 females), Peterson et al. found that sedentary behavior varied significantly; that is, many participants were highly active, while many other participants were highly sedentary. They concluded that age is a factor that does not lend significant insight into one’s propensity for sedentary behavior without consideration of other lifestyle-related factors.

Since 2001, sedentary behavior has increased across all age cohorts (Yang et al., 2019). A large-scale cross-sectional analysis was recently conducted in the United States by Yang et al. to determine trends in sedentary behavior between 2001 and 2016. Among children who participated, the prevalence of spending 2 or more hours sitting leisurely at a computer daily increased from 43% to 57%. Among adults, this metric shifted from 30% to 50%. Time spent watching television remained the same for adults and decreased slightly—but insignificantly—among children. Daily time spent sitting increased for both children and adults, to 7-8 hours for adolescents and 5.5-6.5 hours for adults. The results of this research indicate subtle shifts over time towards increased seated screen time for children/adolescents and increased seated work for adults.

Sedentary behavior is almost exclusively discussed in research studies within the context of health implications. Numerous researchers have found associations between excessive sedentary behavior and negative health outcomes, including obesity and heart complications. The following subsection details the relationship between sedentary behavior and health.

Sedentary Behavior and Health

Numerous researchers have found associations between the amount of sedentary behavior individuals engage in daily and their health (Compernolle et al., 2016; Lavie et al., 2019; Suliga et al., 2018). Many research results demonstrate strong relationships between sedentary behavior, cardiovascular health, weight, physical activity, and weight-related health parameters and concerns (Maher & Conroy, 2016; Wu et al., 2017). Suliga et al. (2018) assessed a sample of 10,367 participants based on their physical and sedentary activity levels. Ther findings revealed that breaking up bouts of sedentary behavior with rigorous physical activity helps prevent metabolic syndrome and its abnormal components, especially in participants who are overweight and obese. The results of this research emphasize the connection between sedentary behavior and metabolic health.

Associations between sedentary behavior and health can vary depending on demographic characteristics. Compernolle et al. (2016) investigated the mediating role of sedentary behaviors between socio-demographic characteristics and BMI among a sample of 3,879 women living in low-income neighborhoods. These authors found that sedentary behaviors differed depending on socio-demographic characteristics; further, associations between BMI and employment status, BMI and birth country, and BMI and education level were mediated by screen time and/or television time. Their results suggest associations between demographic characteristics and specific sedentary behaviors, although these relationships were not fully clarified.

Researchers and health experts alike are particularly concerned about the associations between sedentary behavior and health among children and young adults. The sedentary behavior patterns and habits that young people develop early in life can carry on into adulthood and thus, avoiding excessive sedentary behavior early on can set individuals up to develop better health behaviors (Carson & Kuzik, 2017; Devis-Devis et al., 2017). Researchers such as Devis-Devis et al. are quick to note, however, that sedentary behavior is not necessarily the most significant factor regarding health or obesity prevention among young people. Among a sample of 775 adolescents, Devis-Devis et al. found gendered differences in terms of the amount of sedentary behavior and type of sedentary behavior that was the most frequent. Namely, males were more active than females, and males preferred technology-related sedentary activities while females preferred social sedentary activities. Further, physical activity was negatively associated with obesity among most participants. Approximately 23% of participants were in a different, lower weight class at the end of the study; no participants moved to a weight class that was higher than their initial weight class. Devis-Devis et al. did not find that the shift in weight cluster was a result of decreased sedentary behavior or increased physical activity.

Indeed, numerous misconceptions about sedentary behavior and health among young people have been addressed by previous researchers. While the form of sedentary behavior that may come to mind first where children are concerned is screen time, Hoffmann et al. (2019) found evidence that high levels of sedentary time are not only the result of screen time. Among a sample of 198 primary school students, Hoffmann et al. found that high levels of sedentary time were independent of, and not closely associated with, high levels of screen time. Thus, these researchers concluded that screen time should not be mentioned as synonymous with sedentary behavior among specific age cohorts, such as young children, and reducing screen time should not be treated as an intervention to directly address excessive sedentary behavior.

Misconceptions and misinterpretations of sedentary behavior and associated health implications like the ones noted by Devis-Devis et al. (2017) and Hoffmann et al. (2019) make it pertinent to establish and validate standardized methods for evaluating sedentary behavior. The Sedentary Behavior Questionnaire (SBQ) for adults is one such research instrument that has been validated for use among populations of overweight adults, specifically (Rosenberg et al., 2010). The items of the SBQ assess sedentary behavior based on how much time is spent doing specific sedentary behaviors, on average, on a given weekday or weekend. Rosenberg et al. noted the importance of ensuring sedentary behavior research instruments such as the SBQ are tailored to specific age cohorts (i.e., children or adults), as associations between sedentary behavior and health can shift throughout one's life.

Obesity Prevention Among Young Adults

The last section of the current review of literature centers on the nature of obesity and efforts to prevent obesity among young adults. Important considerations and aspects of addressing obesity among populations of young individuals are discussed. Tools and approaches used to prevent obesity are also emphasized.

Obesity describes a weight that exceeds a healthy range. A BMI above 30 is typically used as an indicator of obesity (Dietz, 2017). While obesity has numerous negative health implications, the BMI at which a specific individual becomes significantly more likely to experience weight-related health complications can vary based on numerous factors. Obesity has been on the rise for multiple decades in many countries including the United States. It is of particular concern among young people, as the longer an individual contends with obesity, the more likely serious health concerns are to emerge (Dietz, 2017). Further, obesity early on in life can set young people up for weight and health struggles for years to come.

The rates and statistics associated with obesity vary considerably by country, ethnicity, age, and several other demographic characteristics. Thus, large-scale survey data are particularly useful when researchers seek to develop an overview and understanding of the extent to which obesity impacts specific populations (Abramowitz et al., 2018; Skinner et al., 2018). A recent study conducted by Skinner et al. (2018) aimed to determine the prevalence of obesity in the U.S. among children ages 2 to 19 years old. Data were gathered from the National Health and Nutrition Examination Survey results from 1999–2016. The analyses revealed that obesity rates among Asian and White children were significantly lower than children of other races, particularly Hispanic and African American children. A positive and linear trend in rates of obesity was apparent among children between 2 to 19 years old across every year included in the survey. In particular, there was a sharp uptick in severe obesity among children between 2 to 5 years old between 2015 and 2016. The results of this research highlight the concerning trends of increased obesity among children and young adults in the U.S. in recent years. Another recent study that centered on obesity trends among pediatric patients was reported on by Yanovski (2018). This scholar analyzed the results of a global study of pediatric obesity between 1975 and 2016, finding that during the analyzed range of years, pediatric obesity rose above 5%, while the rate of underweight children remained above 8% after decreasing slightly. The results of this study indicate the need for continued measures to prevent and address obesity and malnutrition among children globally.

Some contention has occurred within health and research communities due to disagreement regarding the extent to which BMI predicts health complications as a result of excess weight and obesity. Some researchers have contended that a combination of body fat percentage and other weight-related metrics is more accurate to assess obesity or the extent to which excess weight may affect health than comparing height and weight, the two factors used to compute BMI (Abramowitz et al., 2018). For instance, a female bodybuilder who is 5’2” with abnormally high levels of muscle mass and abnormally low levels of body fat would be considered “overweight” based on BMI if her weight exceeded 137 pounds, although this could be an entirely healthy weight depending on her diet and exercise habits. Further, for individuals for which BMI is an effective indicator of healthy weight, there remains a lack of consensus regarding the BMI that is associated with the lowest risk of death. Some researchers have contended that individuals in the normal BMI range are equally as susceptible to mortality. Others, including Abramowitz et al. (2018), have found that individuals with a BMI that still falls within the normal range may be more susceptible to certain health concerns regardless. In the study of Abramowitz et al., the authors determined that for any BMI equal to or above 22, “participants with low muscle mass had higher body fat percentage (%TBF), an increased likelihood of diabetes, and higher adjusted mortality than other participants” (p. 1). Further, the researchers also found in regards to the appendicular skeletal muscle mass index (ASMI) that “excluding participants with low muscle mass or adjustment for ASMI attenuated the risk associated with low BMI, magnified the risk associated with high BMI, and shifted downward the level of BMI associated with the lowest risk of death” (Abramowitz et al., 2018, p. 1). The results of this study highlight the potential value of using additional metrics, such as ASMI, in addition to BMI when seeking to determine a healthy weight range for a specific individual.

Obesity can lead to negative mental health outcomes due to how it influences some individuals’ self-esteem and how they perceive themselves. This impact on mental health is of particular concern among young people who are still forming their self-perceptions and developing mentally (Engür & Karagöl, 2019). A recent comparison study conducted by Engür and Karagöl (2019) centered on determining how body perceptions and self-esteem differ between obese and non-obese adults who visited an outpatient clinic (*n* = 175 obese patients and *n* = 175 nonobese patients). The analyses of patient data and survey results revealed that patients who were obese were more likely to have low self-esteem and less favorable perceptions of their bodies; further, obese patients were more likely than non-obese patients to perceive their body weight as lower than it was. The findings of this research emphasize associations between obesity and negative self-perceptions, which could be of particular concern among young individuals, who are already vulnerable to body image issues.

The negative self-perceptions and mental health implications of obesity are sometimes compounded by the stigma associated with obesity. During childhood, overweight and obese children are often ridiculed by peers due to unconsciously learned weight bias and discrimination (Puhl & Brownell, 2003). As obese children near adulthood, they are similarly likely to encounter weight bias and discrimination when seeking employment, healthcare, education, and throughout everyday life. Puhl and Brownell called for a new theory to help explain weight discrimination and bias, as no existing theory was available. By developing new theoretical propositions and research to understand why obesity is stigmatized, researchers may work towards addressing the stigma surrounding obesity and, ultimately, improving the self-perceptions and mental well-being of individuals impacted by obesity stigmatization.

The first step to develop solutions for obesity prevention among young people is to understand the nature of obesity and the factors that contribute to it; however, some of the complex associations between factors that contribute to obesity among young people are still not well-understood (Gaddad et al., 2018). A recent observational cross-sectional survey of Indian adolescents between 13 and 18 years old was conducted by Gaddad et al. Of the participants, most were normal weight (75%) and none were considered obese. While 77% of all participants did not take part in the recommended amount of physical activity, girls were 11.8% more likely not to exercise enough. Normal or high self-esteem was prevalent among participants. Further, disordered eating behaviors were found in 23.6% of participants. The high prevalence of disordered eating behaviors found during the study of Gaddad et al. suggests the need to conduct further research on eating patterns among young people.

Many researchers have sought solutions to prevent obesity among young people before it occurs, and also to intervene and address obesity which has already developed. As Pandita et al. (2016) noted in a recent study by the same name, however, prevention of childhood obesity is better than curing childhood obesity. The researchers highlighted the efficacy of childhood obesity prevention efforts which are aimed at specific populations. Targeting specific populations for obesity prevention has the added benefit of prevention methods that are tailored to the traits, characteristics, and lifestyles of the individuals who are affected (Pandita et al., 2016). Further, by targeting specific populations, health experts and researchers can ensure that obesity prevention strategies are culturally responsive and able to be realistically implemented for extended periods.

It is a common folly of obesity researchers and health experts to draw questionable causal links between obesity and specific diseases, a folly which sometimes contributes to unsuccessful obesity prevention efforts (Chiolero, 2018; Pandita et al., 2016). While relationships clearly exist between obesity and certain conditions, such as cardiovascular disease, researchers are quick to ignore how these relationships vary depending on demographics and context. Thus, perhaps a means of improving the efficacy of obesity prevention efforts is to merely change and narrow the scope of the predicted implications of obesity prevention efforts. As Chiolero (2018) extrapolated,

> A straightforward implication is that preventing obesity will decrease the number of years lived with diseases. This statement implies a causal link between obesity and these diseases. Although this implication seems evident, stating that we can prevent diseases or delay their occurrence if we reduce obesity raises several complex issues. (p. 461)

The interventions and treatment approaches designed to address obesity require means of tracking and evaluating health metrics and dietary intake. Thus, researchers including Leatherdale and Laxer (2013) have developed research instruments to serve this purpose. The COMPASS questionnaire was developed and tested by Leatherdale and Laxer for assessing dietary intake and weight status as a part of larger intervention studies. Test-retest reliability and concurrent validity for the developed questionnaire led to the determination that the COMPASS questionnaire was a valid and reliable tool for evaluating dietary intake and weight status.

An in-depth understanding of how obesity impacts quality of life in general is also essential to inform effective and realistic intervention and prevention efforts. Laxy et al. (2018) noted that there is significantly more research evidence regarding how obesity impacts health than there is concerning how obesity impacts quality of life. The results of the analysis of pooled, cross-sectional data representing 41,459 respondents who took part in the Medical Expenditure Panel Survey (MEPS) revealed that the BMI range where individuals experience the highest levels of quality of life differed based on age and ethnicity. Namely, men experienced the greatest quality of life at a higher BMI than women, and Hispanic women experienced the greatest quality of life at a higher BMI than White women. The results presented by Laxy et al. emphasize how individuals experience the relationship between weight and quality of life very differently based on demographic characteristics. These findings suggest the need to address the subjective influence of demographic factors during obesity prevention and intervention efforts.

Summary

In summation, the current study centered on exploring how sedentary behaviors moderate the relationship between screen time spent on different types of social media and BMI among young adults in the United States. Thus, the purpose of this quantitative correlational study was to (a) examine the relationship between screen time of different types of social media such as social networking sites, image-sharing sites, discussion sites, and video-hosting sites (Bickham et al., 2013) and an individual’s BMI and (b) determine how sedentariness moderates the relationship between screen time and BMI.

The theoretical framework for this study was Rosenstock's (1974) Health Belief Model. The HBM is rooted in the notion that people improve, change, and adapt their health behaviors as a result of their attitudes and beliefs (Rosenstock, 1974). Previous researchers have used the HBM as a theoretical framework to examine social media and health behaviors (Kite et al., 2018; Zhang et al., 2017), but most HBM research concerning social media has solely centered on the influence of social media as an information source. I hypothesized, based on extant research findings and the core principles of the HBM, that many young adolescents with high BMI avoid in-person socialization and instead prefer frequent social media/screen use and sedentary behavior due to concerns about their peers' weight-related perceptions and biases.

Sedentary behavior occurs when an individual is awake but expends a low amount of energy equal to or less than 1.5 METs (Fukai et al., 2016; González et al., 2017). Since 2001, sedentary behavior has increased significantly among individuals of all ages (Yang et al., 2019). This change reflects a general shift in lifestyle and health behaviors which has progressed over the past two decades, as the lifestyle an individual leads directly determines the extent of their sedentary behavior (Kehler et al., 2018; Peterson et al., 2018). Numerous researchers have discovered relationships between the amount of daily sedentary behavior individuals partake in daily and health (Compernolle et al., 2016; Lavie et al., 2019; Suliga et al., 2018). These associations vary considerably depending on demographic characteristics, particularly race and age (Gavin et al., 2019; Jones et al., 2016).

Social media, a phenomenon that has exploded across the globe in the past decade, consists of applications, websites, and platforms intended for social networking (Fuchs, 2017; Greenwood et al., 2016). Social media use has contributed to a significant lifestyle shift for many people, as it impacts their habits and free time (Alley et al., 2017). The use of different social media platforms is not consistent across age groups, as social media platforms are used for different purposes and entice different types of people (Greenwood et al., 2016). The ever-increasing popularity of social media has led to increased research on how social media use affects health (Bekalu et al., 2019; Melkevik et al., 2015). Researchers and health experts alike are worried about how social media influences young people because their brains are still developing and are more prone to be influenced than those of adults. The habits and lifestyle shifts associated with frequent use of social media have been shown to detrimentally impact physical health in some research contexts (Melkevik et al., 2015). Despite these concerns, social media has also been used as a tool for improving health and wellness during intervention studies (Gabarron et al., 2018).

Understanding the nature of obesity and the factors that contribute to it are key to developing obesity prevention solutions to help young people establish healthy lifestyles. Interventions and treatment approaches that are aimed at addressing obesity often require tools and research instruments to record health metrics and dietary intake, though the validity and reliability of these instruments vary (Leatherdale & Laxer, 2013). Realistic obesity intervention and prevention efforts also require an in-depth understanding of how obesity impacts one's quality of life, as well as how demographic variables impact how obesity is experienced (Laxy et al., 2018). Many researchers have studied associations between screen time, sedentary behaviors, health, and/or obesity (Bosch et al., 2019; Falbe et al., 2017; Wachira et al., 2018); however, there remains a lack of insights regarding these relationships as they exist among young adults where social media screen time is concerned.

In Chapter 3, I provide a detailed description of the research methods that were selected for the current study. This includes details on the research design, sample selection, data analysis strategy, and ethical considerations. A summary and a transition to the remainder of the dissertation conclude the chapter.

Chapter 3: Research Method

Introduction

The purpose of this quantitative correlational study was to (a) examine the relationship between screen time on different types of social media (social networking sites, image-sharing sites, discussion sites, and video-hosting sites) and an individual's BMI and (b) determine how sedentariness moderates the relationship between screen time and BMI. Screen time on different types of social media was considered as the predictor variable, sedentariness as the moderating variable, and BMI as the criterion variable. The target population included young adults aged 18 to 25 years old who were fluent in English and living in the United States. For the purposes of this study, screen time refers to the time individuals spend on social media through websites and/or using electronic devices including phones, televisions, and computers. Social media platforms are applications and websites that can be used for social networking (Fuchs, 2017). The social media platforms that were considered for this study included social networking sites, image-sharing sites, discussion sites (school or nonschool related), and video-hosting sites. Popular social media platforms include Facebook, Twitter, Snapchat, Instagram, and TikTok, to name a few. This study is particularly important as a means of assessing the degree to how much time is spent on specific types of social media and what lifestyle changes young adults should do to lower their chances of developing obesity-related health risks.

In this section, I present the selected research method and design and explain their appropriateness for this study. In addition, I provide a detailed discussion of the target population and sampling strategies used, as well as the specific data collection and data analysis procedures. I then discuss the threats to validity and ethical procedures that were followed. A summary of the key points of the proposed methodology concludes the chapter.

Research Design and Rationale

The quantitative method was employed for the current study. Quantitative methods have been described as requiring the use of mathematical techniques to provide statistical inferences about the relationships or differences on numerically measured variables (Camm, 2012; Hancock & Mueller, 2010; Wisniewski, 2016). The quantitative methodology is normally used on studies that have research questions pertaining to "who," "what," and "how many" (Leavy, 2017). Within the quantitative method, a correlational research design was selected. Correlational research designs allow scholars to determine the relationships between numerically measured variables (Curtis et al., 2016; Goodwin & Goodwin, 2013). The use of a correlational research design provided an opportunity for me to evaluate both the magnitude and behavior of the relationships between the study variables (see Leedy & Ormrod, 2012; Whitley et al., 2013). Through the use of the quantitative method with correlational research design, insights on how sedentariness (the moderating variable) impacts the relationship between screen time on different types of social media (the predictor variable) and BMI (the criterion variable) were obtained through moderated regression analysis. The results of these analyses allowed me to answer the research questions and hypotheses of the study.

Other research designs such as causal comparative and experimental were deemed to be inappropriate for the study. A causal-comparative research design primarily explains the differences of means of a dependent variable across two or more groups (Babbie, 2013; Rottman & Hastie, 2014). This study only focused on one group of participants (i.e., young adults 18-25 years old in the United States) that were measured at one point in time. An experimental approach was not appropriate for the current study due to the use of a hypothesis (or several hypotheses) to affirm whether a treatment or experiment affect a variable or variables (Babbie, 2013; Hoe & Hoare, 2012). I did not conduct any treatment or experiment with the selected young adults, and only focused on their existing characteristics. Causal comparative and experimental research designs were, therefore, inappropriate for the objectives of this study.

Methodology

Population

The target population for this study included young adults aged 18 to 25 years old in the United States. As of 2019, there were 328,239,523 U.S. citizens, with 30,373,170 within the similar range of 18 to 25years old, representing 9.3%of the total U.S. population (U.S. Census Bureau, 2020).

Sampling and Sampling Procedures

I used random sampling to recruit the participants. Random sampling allows me to identify the pool of volunteers for the study and then select the desired sample size from this pool and in which each volunteer has an equal probability of being chosen (Creswell, 2012). It also allows researchers to generalize from the sample being studied in addition to being able to add participants at any time in the research process if needed (Creswell, 2012). The random sampling methodology is consistent with the sample frame of the study, which only included young adults in the United States. The inclusion criteria for this study were: (a) being 18 to 25 years old, (b) being fluent in English, and (c) living in the United States. After the survey collection was closed, SPSS was used to randomly select the required sample size for the study from the entire survey response dataset.

The required sample size was determined by conducting a power analysis using G*Power software (see Faul et al., 2013). The four factors considered in the power analysis were significance level, effect size, power of test, and statistical test. Significance level refers to the probability of rejecting a true null hypothesis, also commonly called a Type I error (Haas, 2012). The power of test refers to the probability of rejecting a false null hypothesis (Haas, 2012). In most quantitative studies, the significance level is set at 95% and the power of test is set at 80%, (Koran, 2016). I used these suggested levels during the G*Power analysis. The effect size indicates the estimated degree of relationship between predictor and criterion variables (Cohen, 1988). Effect sizes are normally categorized as either small, medium, or large (Berger et al., 2013). Several researchers who examined screen time among young adults used a small effect size in their respective studies (e.g., Cammack et al., 2020; Montagni et al., 2016; Rosenberg et al., 2010; Saquib, 2018; Shrivastava & Shrivastava, 2019). Lastly, I used multiple regression analysis to address the research questions and test the hypotheses. Using 95% significance level, 80% power of test, a medium effect size (f^2 = .20), and multiple regression analysis with eight predictors, I determined that the minimum required sample size was 120; this minimum was exceeded by the actual sample size of 135.

Procedures for Recruitment, Participation, and Data Collection

Before any data collection began, I secured institutional review board (IRB) approval. IRB approval from Walden University was obtained, and all approval conditions followed. After securing IRB approval, the data collection plan was conducted as follows. Young adults were contacted through social media platforms such as Facebook, Instagram, Twitter, and the Walden subject pool. Those individuals who were interested in the research project proceeded to the study website hosted by Qualtrics. Initially, potential participants were presented with an online consent form to describe the study, assure the participants of the anonymity of their responses, and seek their informed consent. The informed consent form contained a brief description of the study, the risks and benefits for participating, the role of the participants, the withdrawal procedures, and my contact information. Only those individuals who met the eligibility criteria were allowed to proceed to the survey measures, which could be completed in approximately 15 minutes. The eligibility criteria for this research applied to a large number of potential participants who were accessible online; accordingly, I did not anticipate that obtaining a sufficient sample size would be difficult, but planned to use additional social media platforms to obtain additional respondents if necessary.

After completion of the survey, the participants were directed to a page that thanked them for their responses. The data files were securely protected by Qualtrics and sent electronically to the me for analysis using Statistical Package for the Social Sciences

(SPSS) software. The collected data were imported using IBM's SPSS v. 25 to facilitate data analysis.

Instrumentation and Operationalization of Constructs

I used two instruments to gather relevant data: the SBQ (Rosenberg et al., 2010) and a self-developed questionnaire consisting of BMI, social media screen time, and demographic questions. The SBQ was originally a measure used in children that has some evidence of reliability and validity (Norman et al., 2005). It was designed to assess the amount of time spent doing nine behaviors: watching television, playing computer/video games, sitting while listening to music, sitting and talking on the phone, doing paperwork or office work, sitting and reading, playing a musical instrument, doing arts and crafts, and sitting and driving/riding in a car, bus, or train. These nine behaviors were assessed separately for weekdays and weekend. Response options included *none*, *15 minutes or less*, *30 minutes*, *1 hour*, *2 hours*, *3 hours*, *4 hours*, *5 hours*, or *6 hours or more*.

The time spent on each behavior was converted into hours (e.g., a response of 15 minutes was recoded as .25 hours). For the total scores of sedentary behaviors, hours per day for each item were summed separately for weekday and weekend days. The weekly hourly estimate was computed by multiplying the weekday hours by five and multiplying weekend hours by two; these were then summed for total hours/week. For the summary variables of total hours/day spent in sedentary behaviors (weekday and weekend) and total sedentary hours/week, responses higher than 24 hours/day were truncated to 24 hours/day. For this study, terminologies such as *children* were revised to *young adult* to suit the target population. Rosenberg et al. (2010) reported that their revised SBQ has moderate to excellent reliability for weekdays (Cronbach's alpha of .64 to .90) and weekend (Cronbach's alpha of .51 to .93). Furthermore, Rosenberg et al. tested the criterion validity of the questionnaire they have reported significant correlation of SBQ scores with the accelerator mins with counts < 100, accelerometer total activity mins/day, and IPAQ total sitting time. A copy of the SBQ is in Appendix A. No permission was needed to use the SBQ.

The other questionnaire contained three parts: BMI, social media screen time, and demographics. For the BMI part, there were two questions: height and weight. I then computed the BMI from these two parameters. The screen time section contained questions regarding how much screen time an individual spends on each of the types of social media. The types of social media are social networking sites (e.g., Facebook, dating sites, etc.), image-sharing sites (e.g., Instagram, Flickr, 500px, etc.), discussion sites (e.g., school or non-school related such as university discussion boards, technology discussion boards, opinion and news sites, etc.), and video-hosting sites (e.g., YouTube, Vimeo, Dailymotion, etc.). The individuals provided their response from nine choices. The nine choices are the same as those in the SBQ. The computation was the same for SBQ, except that there was no differentiation between weekday and weekend. Finally, the demographic part contained four items that asked about gender, age, race, and highest educational attainment. A reliability coefficient was computed for the scale items, and SPSS was used to compute this statistic. This questionnaire is in Appendix B.

Data Analysis Plan

The data analysis for this study was performed using SPSS for Windows to provide a range of descriptive as well as inferential statistics, including statistical correlations. SPSS software is used extensively by researchers in the educational as well as social and behavioral sciences (Hinton et al., 2014). The advantage of using SPSS is that it is user friendly and enabled me to export data from Microsoft Excel easily. All required statistical tests for this study were conducted in SPSS.

All data were preprocessed. Preprocessing aims to ensure a clean dataset by excluding data outliers and missing data. Only those participants who provided complete information on all the variables were included in the data analysis. If a value was missing, the entire case was removed from the analysis (i.e., listwise deletion). In listwise deletion, a case is dropped from an analysis because it has a missing value in at least one of the specified variables. The complete, clean dataset was utilized for data analysis 29 participants were removed in total.

The following are the research questions and corresponding hypotheses that were addressed in this study:

RQ1: Do relationships exist between screen time on the different types of social media (social networking sites, image-sharing sites, discussion sites, and video-hosting sites) and an individual's BMI?

$H_0$1: There is no significant relationship between screen time on the different types of social media and an individual's BMI.

H_a1: There is a significant relationship between screen time on the different types of social media and an individual's BMI.

RQ2: Does sedentariness moderate the relationship between screen time on the different types of social media and an individual's BMI?

H_02: Sedentariness does not significantly moderate the relationship between screen time on the different types of social media and an individual's BMI.

H_a2: Sedentariness significantly moderates the relationship between screen time on the different types of social media and an individual's BMI.

Descriptive analyses were conducted first in order to characterize the demographics of the participants as well as their responses to the survey. Descriptive statistics such as frequency, percentage, mean, and standard deviation were computed. Charts such as pie charts and histograms were generated to accompany the descriptive analysis.

The data plan included inferential statistical analyses, specifically multiple linear regression analysis, to examine the relationship between screen time on different types of social media as well as how sedentariness moderates the relationship between screen time and BMI. Regression analysis serves three purposes: description, control, and prediction (Nimon & Reio, 2011). To perform the regression analysis with the moderating variable, new interaction variables with the predictors and the moderator were created. To create the interaction variables, the predictors (social networking sites, image-sharing sites, discussion sites, and video-hosting sites) were centered and combined with the sedentariness variable score, resulting in four new interaction variables (Field, 2013).

Assumption violations were checked when regressing the four new variables on the DV (BMI).

Because multiple linear regression analysis is considered a parametric test, certain assumptions must be met first before it can be used. There are four assumptions of parametric tests: (a) normality, (b) homogeneity of variance, (c) linearity, and (d) independence (Sedgwick, 2015). A Kolmogorov-Smirnov test was performed in order to determine whether all study variables comply with the normality assumption (Siddiqi, 2014). Second, a test for homogeneity of variance was conducted using Levene's test that investigates for a constant variance of error for the independent variable, by plotting residuals versus predicted values, and residuals versus independent variables (Parra-Frutos, 2013). If the scatterplots of the variables are pattern-less, it suggests that the error is consistent across the range of predicted values hence the assumption is met. Third, a linearity test was conducted to test for a linear relationship between the two variables (Sedgwick, 2015). The linearity test involved producing scatterplots in order to make sure the mean of the outcome variable for each increment fell on a straight line. Lastly, a test for outliers was conducted through visual inspection of histograms and box-plots in order to meet the assumption of independence (Huber & Melly, 2015).

Hypothesis testing was done on all analyses using an 0.05 level of significance (Weakliem, 2016). This means that all *p*-value outputs of the hierarchical multiple regression were assessed using a .05 level of significance. A *p*-value of less than .05 for dictates that there is a statistically significant relationship between the variables, meaning that the null hypothesis is rejected. In contrast, a value of greater than .05 dictates that there is no statistically significant relationship between variables, leading to the acceptance of the null hypothesis.

Threats to Validity

Researchers must recognize and mitigate the threats to validity for their study. Three threats affecting this research study are construct, internal, and external validity. Addressing the threats strengthens the study, validates the research design method, and ensures that the study is measuring what it claims to measure (Shadish et al., 2002).

Internal validity is the extent to which I can conclude that the findings of the study are true (Leedy & Ormrod, 2012). O'Dwyer and Bernauer (2016) defined internal validity as the approximate truth about inferences regarding cause-effect or causal relationships. O'Dwyer and Bernauer continued to explain that the key question in interval validity is whether observed changes can be attributed to an intervention, the cause or independent variable, and not to other possible causes or alternative explanations. If a study has a high degree of internal validity, then I can conclude strong evidence of causality. Specific to this study, threats to internal validity in correlational research designs include the issue of data normality and the existence of cofounding variables (Tharenou et al., 2007). To help mitigate the internal validity threat of instrumentation, the study only included valid and reliable instruments. In addition, I assumed that the respondents would provide honest responses regarding their screen time on each of the different types of social media. Only volunteers proceeded to the survey questions, and participants were free to stop responding at any time; therefore, it is a valid assumption that volunteers who went through all the survey items were willing to provide screen time information. With regards to the validity of the BMI responses, I evaluated the general data trustworthiness by comparing the responses to the national indices for BMI as a benchmark. Respondents were given 1 week only to complete the survey; as such, the internal validity threat of design contamination, history, and maturation should be minimized.

External validity is related to generalization of results to a larger population (O'Dwyer & Bernauer, 2016). The design of this study did not allow me to generalize results beyond the study population. Moreover, external validity threat in this study includes the interaction of the relationship with settings and bounded by the age of the age of the participants (Tharenou et al., 2007). Tharenou et al. (2007) stated that the interaction of relationship with settings indicates whether one kind of setting will hold if done in a different setting. As this study's population was based on the where the young adults reside, the interaction of relationship with setting could limit the generalization of the findings to other population based on age.

Ethical Procedures

Before beginning data collection, I obtained IRB approval from the university to ensure that all ethical standards were met. (Walden University's approval number for this study is 03-18-21-0477621 and it expires on March 17, 2022.) The research was not expected to pose any harm to participants for several reasons. Firstly, the nature of anonymous quantitative data collection was such that no identifying information was collected that could be linked back to the participant. Pseudo codes were used to designate each participant (i.e., P01 for the first participant, etc.). Secondly, young adults are not a vulnerable population. The data that were collected in this study were not in any way confidential, meaning that were anonymity somehow compromised, the risk of harm would remain minimal.

Hard copies of raw data and other documents pertinent to the study were securely kept in a locked filing cabinet inside my personal office. Soft copies of raw data and other documents were saved in a password-protected flash drive. All data and documents related to the study will be destroyed 7 years after the study's completion; at this time, hard copies of the data will be shredded, and soft copies will be deleted.

Summary

The purpose of this quantitative correlational study was to examine (a) the relationship between screen time on different types of social media (social networking sites, image-sharing sites, discussion sites, and video-hosting sites) and an individual's BMI and (b) determine how sedentariness moderates the relationship between screen time and BMI. The screen time on different types of social media was considered as the predictor variable, sedentariness as the moderating variable, and BMI as the criterion variable. The target population included young adults ages 18 to 25 years old in the United States. I used two instruments to gather relevant data: the Sedentary Behavior Questionnaire (Rosenberg et al., 2010) and a self-developed questionnaire consisting of BMI, social media screen time, and demographic questions. A total of 135 young adults were recruited to participate in an online survey. SPSS was used to select the sample size randomly from the complete set of responses to the online survey. Multiple linear regression analysis was conducted in SPSS to analyze the gathered data. In Chapter 4, I will present the results of the data analysis. Chapter 5 includes a discussion of conclusions based on the findings and recommendations for future research.

Chapter 4: Results

Introduction

The purpose of this analysis was to examine the relationship between screen time on different types of social media and an individual's BMI and to determine how sedentariness moderates the relationship between screen time and BMI. Exploratory data analysis was performed to provide a description of the sample's demographic characteristics. Then, correlation analysis and a linear regression model with an interaction effect were implemented to test the hypotheses and answer the research questions. The assumptions of linear regression were tested prior to conducting this analysis.

Research Questions and Null Hypotheses

RQ1: Do relationships exist between screen time on the different types of social media (social networking sites, image-sharing sites, discussion sites, and video-hosting sites) and an individual's BMI?

RQ2: Does sedentariness moderate the relationship between screen time on the different types of social media and an individual's BMI?

Data Collection

Descriptive Statistics

The final dataset consisted of 135 participants. These participants provided data regarding their weight, height, screen time on four types of social media, sedentary behavior, and demographic characteristics. The BMI score was created using the following formula:

$$\text{weight (lb)} / [\text{height (in)}]^2 \times 703$$

The sample consisted of 75 females and 60 males. The most common educational attainment level was a high school diploma (41.5%), followed by a Bachelor's degree (26.6%) and an Associate's degree (25.9%); the rest (6.0%) held a Master's degree or had completed some high school. Most participants (51.1%) were between 22 and 25 years old. White participants accounted for 65.1% of the sample, followed by Asians (15.6%) and African Americans (11.9%); American Indians and Pacific Islanders represented 7.4% of the sample (see Table 1).

Table 1

Sociodemographic Characteristics of Participants

	N	%
Gender		
Female	75	55.6%
Male	60	44.4%
Education		
Associate's degree	35	25.9%
Bachelor's degree	36	26.6%
High school diploma	56	41.5%
Master's degree/Doctorate degree	4	3.0%
Some high school	4	3.0%
Age		
18 – 21	66	48.9%
22 – 25	69	51.1%
Race (Ethnic groups)		
American Indian or Alaska Native	7	5.2%
Asian	21	15.6%
Black or African American	16	11.9%
Native Hawaiian or Other Pacific Islander	3	2.2%
White	88	65.1%

Note. https://www.cdc.gov/nccdphp/dnpao/growthcharts/training/bmiage/page5_2.html

Reliability and Validity

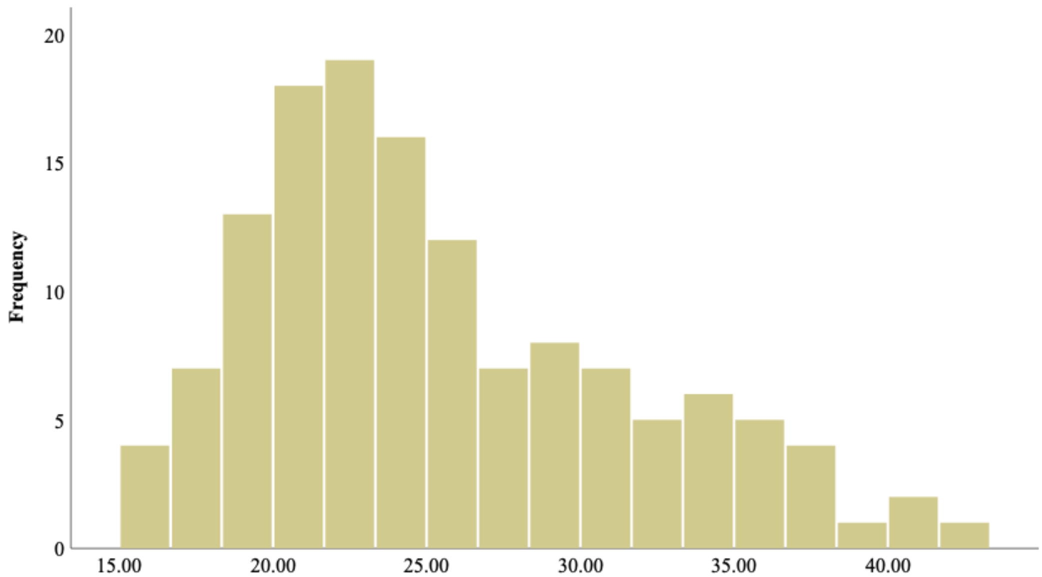
To perform the correlation and regression analyses, the composite score of the responses to sedentary behavior questions was created. To address the reliability of data, I conducted Cronbach's analysis on the composite score. The alpha level for the composite score was .785, indicating that the variable had an adequate level of reliability and internal consistency in measuring the constructs of the study. To test the validity, a correlation analysis of the responses and corresponding composite score was performed. The results revealed a strong significant correlation between the variables and composite score (r (133) > .3, p < .01).

Tests for Normality

The average weight of participants was 158.87 pounds (*SD*=43.69) and the average height was 66.22 inches (*SD* = 4.33). The BMI outcome variable had an average score of 25.40 (*SD* = 6.09; Figure 1). The distribution was positively skewed, and the Shapiro-Wilk test returned W (135) = .95, p < .01, indicating that the variable was not normally distributed.

Figure 1

Distribution of BMI



The predictor variables measuring time spent on different types of social media returned a significant Shapiro-Wilk test coefficient, indicating that the variables were not normally distributed (see Table 2).

Table 2

Shapiro-Wilk Normality Test

	Statistic	df	Sig.
Networking	.904	135	<.001
Image	.838	135	<.001
Discussion	.766	135	<.001
Video	.868	135	<.001
Sedentary Behavior	.936	135	<.001

Results

Hypotheses

$H_0$1

Based on the results of tests of normality, I conducted a nonparametric Spearman's Rho correlation analysis. The results indicated that an individual's BMI was not significantly correlated with time spent on different types of social media and sedentary behavior (see Table 3). It was found that sedentary behavior was moderately positively correlated with time spent on several types of social media, particularly image, discussion, and video (r (133) > .2, p < .05). This led me to conclude that more time spent on these types of social media was significantly correlated with more time associated with sedentary behavior.

Table 3

Spearman's Rho Correlation Analysis

	BMI	Networking	Image	Discussion	Video	Sedentary
BMI	-					
Networking	-.06	-				
Image	-.01	.53**	-			
Discussion	-.08	.10	.31**	-		
Video	-.09	.33*	.25**	.12	-	
Sedentary	-.01	.06	.21*	.36**	.28**	-

* $p < .05$ ** $p < .01$

Multiple linear regression was performed to estimate the marginal effect of the predictor variables on BMI. The model explained 3% of the variability in the outcome variable. The overall summary of the model showed that the effect was nonsignificant (F (4, 130) = 0.99, $p = .41$). The predictor variables were nonsignificant in explaining the variability of the body mass index (see Table 4).

Table 4

Multiple Regression Model Coefficients

Model	B	SE	Beta	t	Sig.
(Constant)	26.51	0.99		26.83	<.01
Networking	-0.25	0.34	-.07	-0.73	.46
Image	0.44	0.40	.11	1.11	.27
Discussion	-0.50	0.46	-.10	-1.09	.28
Video	-0.35	0.30	-.11	-1.15	.25

$H_0 2$

Hierarchical multiple linear regression was conducted to test whether sedentary behavior moderated the relationship between screen time on the different types of social media and an individual's BMI. Model 1 assessed the effect of centered different types of social media and the centered composite score of sedentary behavior on BMI. Model 2 introduced the interaction terms of centered different types of social media and the centered composite score of sedentary behavior to the regression model (see Table 5).

Table 5

Hierarchical Linear Regression Models

Model	Variable	B	Std. Error	Beta	t	Sig.	VIF
1	(Constant)	25.40	0.52		48.49	<.001	
	Network	-0.21	0.34	-.06	-0.62	.54	1.40
	Image	0.38	0.41	.10	0.93	.36	1.45
	Discussion	-0.69	0.50	-.14	-1.38	.17	1.29
	Video	-0.41	0.31	-.12	-1.32	.19	1.19
	Sedentary	0.91	0.89	.10	1.02	.31	1.31
2	(Constant)	25.61	0.59		43.29	<.001	
	Network	-0.23	0.35	-.07	-0.66	.51	1.43
	Image	0.49	0.44	.13	1.11	.27	1.67
	Discussion	-0.73	0.55	-.14	-1.33	.19	1.53
	Video	-0.37	0.32	-.11	-1.15	.25	1.24
	Sedentary	0.86	0.93	.10	0.93	.36	1.39
	Net_Seden	0.02	0.50	.00	0.04	.97	1.51
	Image_Seden	-0.37	0.63	-.07	-0.58	.56	1.94
	Disc_Seden	0.20	0.80	.03	0.24	.81	1.88
	Vid_Seden	-0.56	0.53	-.10	-1.05	.30	1.19

Dependent Variable: BMI

I concluded that both models were nonsignificant in explaining the variability of the body mass index (see Table 6).

Table 6

Hierarchical Models Summary

Model	R	R^2	Adj R^2	R^2 Change	F Change	p-value
1	.19	.04	0.00	0.037	1.0	.42
2	.23	.05	-0.02	0.014	0.4	.76

1. Predictors: (Constant), SB_AVERAGE, Net_center, Vid_center, Disc_center, Im_center
2. Predictors: (Constant), SB_AV_CENTR, Net_center, Vid_center, Disc_center, Im_center, VID_N_inter, NeT_N_inter, DISC_N_inter, IMG_N_inter

Dependent Variable: BMI

Additional Exploratory Analyses

The relationships between demographic variables and the dependent variables of BMI and sedentary behavior were explored. The results of the nonparametric tests indicated no significant differences on the dependent variables as a function of gender, education, and age. The analyses did reveal significant differences on sedentary behavior as a function of race. The lowest median time associated with sedentary behavior was among the White ethnic group, and the highest medium time was among American Indians (see Table 7 and Figure 2).

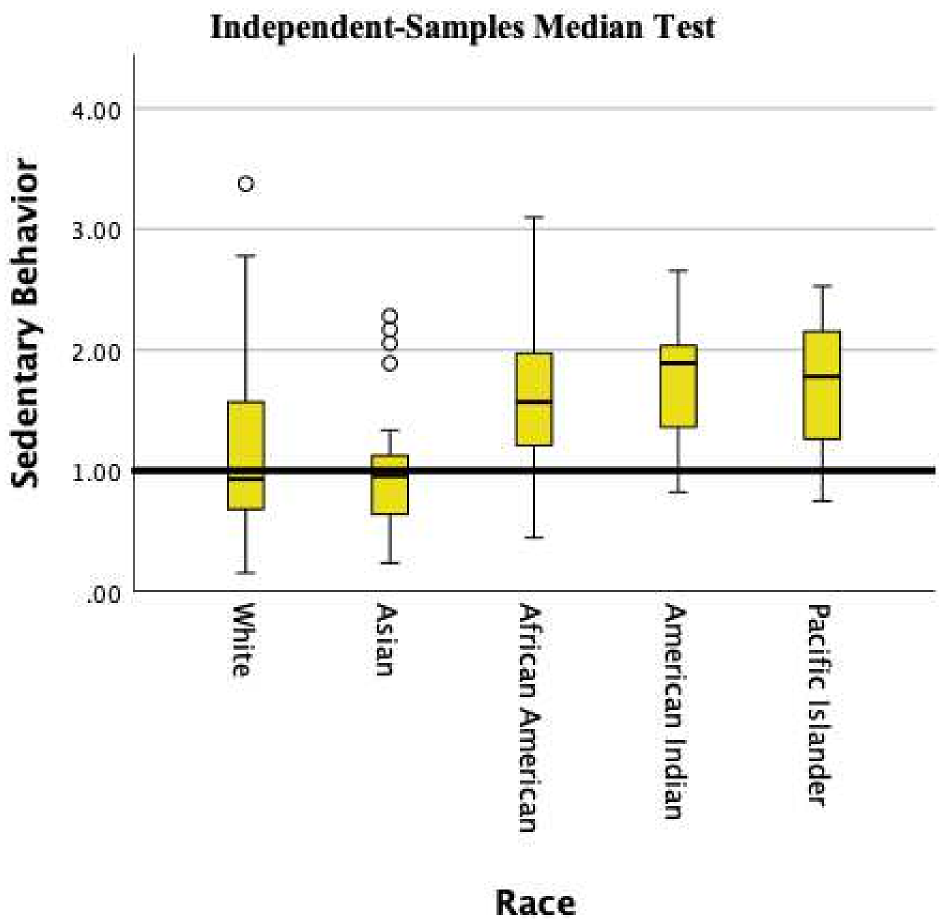
Table 7

Summary Statistics

Race	Mean	Median	*N*	Std. Deviation
1 White	1.13	.93	88	.65
2 Asian	1.05	.96	21	.58
3 African American	1.60	1.57	16	.69
4 American Indian	1.74	1.89	7	.67
5 Pacific Islander	1.69	1.78	3	.89
Total	1.22	1.00	135	.68

Figure 2

Boxplots of Sedentary Behavior Time with Respect to Ethnic Groups



Based on the results of tests of normality, the nonparametric Mood's median test was performed. The results of this test showed that ethnic groups significantly affected the amount of time associated with sedentary behavior (M (4) = 11.28, p = .024). The following pairwise comparison revealed that the difference among the ethnic groups was significant only between the Asian and African American ethnic groups after it was adjusted by the Bonferroni correction for multiple tests (see Table 8).

Table 8

Pairwise Comparisons of Ethnic Groups

Sample 1-Sample 2	Test Statistic	Sig .	Adj. Sig
1 White-2 Asian	.08	.77	1.00
1 White-3 African American	7.39	.01	.07
1 White-5 Pacific Islander	.37	.54	1.00
1 White-4 American Indian	1.60	.21	1.00
2 Asian-3 African American	9.58	.00	.02*
2 Asian-5 Pacific Islander	.38	.54	1.00
2 Asian-4 American Indian	1.71	.19	1.00
3 African American-5 Pacific Islander	.53	.47	1.00
3 African American-4 American Indian	2.25	.13	1.00
5 Pacific Islander-4 American Indian	.08	.78	1.00

Assumption Tests

The outcome variable was measured on a continuous scale. The Durbin-Watson coefficient was 2.35, indicating the absence of autocorrelation. The regression model showed linear relationships. The residual plot showed independence of observation and homogeneity of variance (see Figure 3). The variance inflation factor (VIF) was less than 2 for every coefficient, indicating the absence of multicollinearity. There were no extreme outliers in the data. The residuals were approximately normally distributed (see Figure 4).

Figure 3

Scatterplot of Residuals

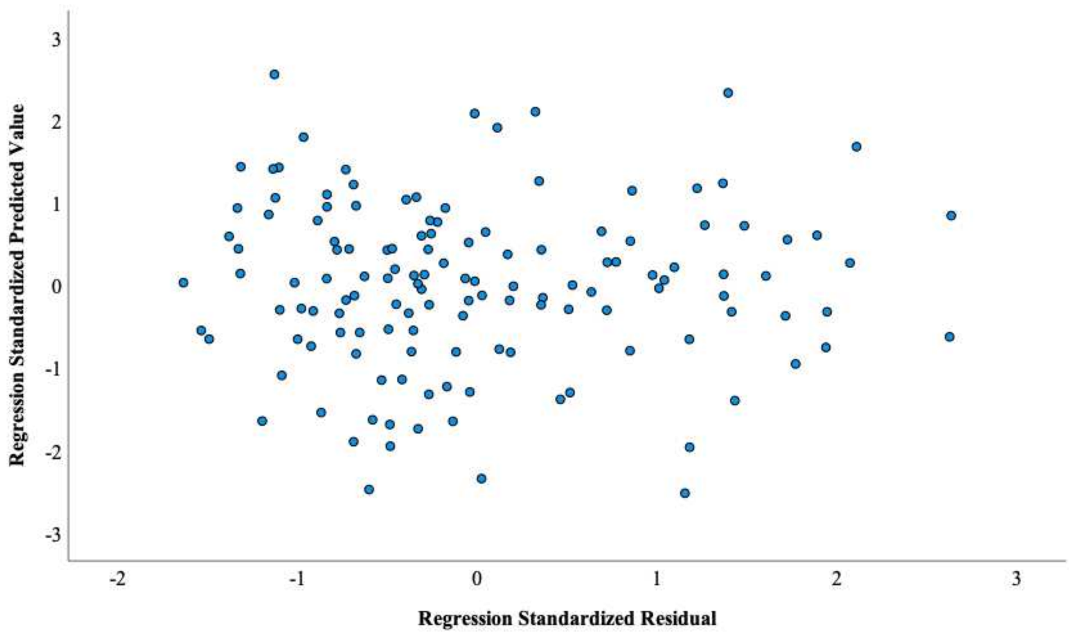
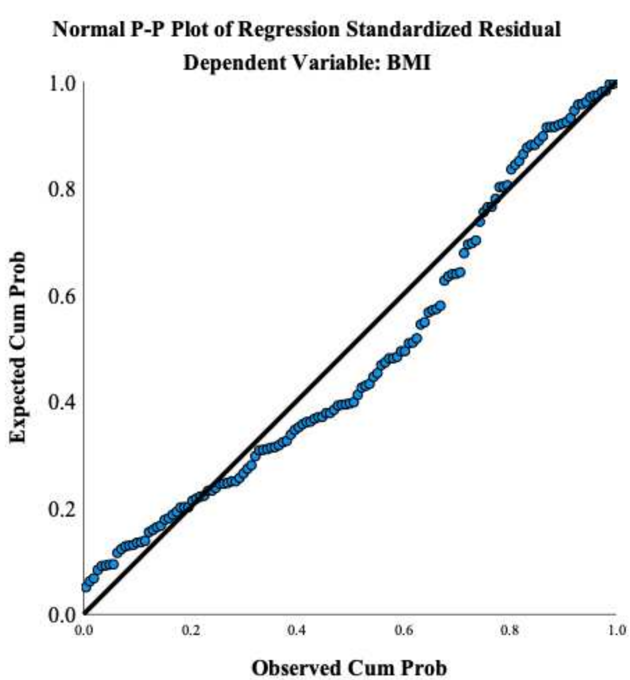


Figure 4

Distribution of Residuals



Summary

The purpose of this analysis was to examine the relationship between screen time on different types of social media and an individual's BMI and to determine how sedentariness moderates the relationship between screen time and BMI. To answer the research questions, a composite score for sedentary behavior was created and multiple linear regression analysis and hierarchical multiple regression analysis were conducted. The results of the statistical analysis showed that there was not enough evidence to reject the first null hypothesis (F (4, 130) = 0.99, p = .41), indicating that the relationships between screen time on different types of social media and an individual's BMI were not statistically significant. There was also not enough evidence to reject the second null hypothesis (F (9, 125) = 0.75, p = .66), which posited that sedentariness did not significantly moderate the relationship between screen time on the different types of social media and an individual's BMI. The assumptions of linear regression were generally met. Through additional analyses on race, I found that ethnic groups significantly affected the amount of time associated with sedentary behavior (M (4) = 11.28, p = .024); however, the following post hoc pairwise comparison analysis revealed that the difference among the ethnic groups was significant only between the Asian and African American ethnic groups after it was adjusted by the Bonferroni correction for multiple tests. In Chapter 5, I will discuss the conclusions of the study and presents a set of recommendations for future research.

Chapter 5: Discussion, Conclusions, and Recommendations

Introduction

In view of the notable lifestyle changes that have recently materialized because of robust new technologies and media forms (Alley et al., 2017), the purpose of the current study was to establish the nature of the relationship between device screen time on social media, BMI, and sedentary behavior for young U.S. adults aged between 18 and 25 years old. Social media screen time was definitively restricted to the time that an individual spends consuming electronic media using gadgets such as phones, televisions, and computers (Christensen et al., 2016), whether actively or simultaneously alongside other activities. Sedentary behavior describes when an individual is awake but expending 1.5 or fewer METs by lying down or sitting (Fukai et al., 2016; González et al., 2017; Tremblay et al., 2017). The BMI is an estimate of an individual's body fat that is calculated based on one's height and weight (Jackson & Cunningham, 2017).

Having established from research that at least 86% of Americans enjoy consistent access to the Internet (Greenwood et al., 2016), a unique dilemma is attributed to growing concerns of how sedentary behavior mediates the relationship between screen time invested in varied social media and BMI among adults. The main supposition established from related research is that excessive sedentariness, screen time, and/or social media use is linked to damaging health consequences such as obesity, BMI scores above 25, depressive symptoms, and poor sleep quality (Chow, 2017; Jackson & Cunningham, 2017; Twenge, Joiner, et al., 2018). A missing element in previous studies on screen time and health-related sedentary behaviors (Bosch et al., 2019; Falbe et al., 2017; Wachira et al., 2018) is the deficiency in perception of these relationships within this population.

The purpose of this quantitative correlational study was two-fold. First, I aimed to establish the relationship between screen time on diverse social media and an individual's BMI. Social media, within the confines of this research, included social networking sites, image-sharing sites, discussion sites, and video-hosting sites, whereas screen time was that simultaneous or asynchronous time spent actively using electronic gadgets to access diverse social media. Secondly, I intended to determine how sedentariness moderates the relationship between screen time and BMI. The methodology involved administering an online survey consisting of the SBQ with additional questions about BMI, social media screen time, and participant demographics.

The results of the analyses to answer the first research question revealed that there was no statistically significant relationship between screen time on diverse social media and an individual's BMI. This means that the difference, equal to or larger than that observed between these two variables, is expected to occur more than one out of 20 times (i.e., the p-value is greater than .05). This finding did not support the study's first alternative hypothesis, which supposed that there is a noteworthy relationship between social media screen time and an individual's BMI.

Further, the outcome of the second research inquiry established that sedentariness did not significantly abate the relationship between screen time on diverse social media and a participant's BMI. Like the findings in the first research inquiry, the results failed to support the second alternative hypothesis, which posited that sedentariness does moderate the relationship between social media screen time and an individual's BMI.

An additional finding was indicated when considering the participant demographics. The results indicated that there is statistical significance in the relationship between ethnic groups and amount of time associated with sedentary behavior. Particularly, having adjusted the model by the Bonferroni correction for multiple tests, the significance of this observation was distinctively unique to the Asian and African American races. In this case, there is less than 5% chance that the observed differences between variable of race and sedentary behavior are expected to occur.

In summary, having tested the two main research questions, the findings indicated there was a failure to reject the null hypothesis in both cases. There is no strong correlation between an individual's BMI, social media screen time, and sedentary behavior, except when demographic variables narrow down to individuals of Asian and African American origin.

Interpretation of the Findings

As introduced in the precursory subsection, the study was organized and guided by two main research questions and corresponding hypotheses:

RQ1: Do relationships exist between screen time on the diverse social media (social networking sites, image-sharing sites, discussion sites, and video-hosting sites) and an individual's BMI?

> $H_0 1$: There is no significant relationship between screen time on the diverse social media and an individual's BMI.

H_a1: There is a noteworthy relationship between screen time on the diverse social media and an individual's BMI.

RQ2: Does sedentariness moderate the relationship between screen time on the diverse social media and an individual's BMI?

H_02: Sedentariness does not significantly moderate the relationship between screen time on the diverse social media and an individual's BMI.

H_a2: Sedentariness significantly moderates the relationship between screen time on the diverse social media and an individual's BMI.

Research Question 1

The first research question was "Do relationships exist between screen time on diverse social media and an individual's BMI?" With the corresponding null hypothesis I theorized that there is no significant relationship between screen time and an individual's BMI. Following data collection and analysis, the resulting lack of a statistically significant relationship between screen time and BMI confirms the research findings of Bickham et al. (2013), which similarly investigated young adolescents' screen media use on television, computers, and video games. These authors' findings established that neither duration of use nor attention paid to video games or computers was associated with BMI. Nonetheless, the difference between the study by Bickham et al. and the current study is in the intended demographic, with young adolescents in the former and young adults in the latter. In contrast, Wachira et al. (2018) established that screen time was indeed associated with percent body fat—but only over weekends, when participants who qualified as obese reported higher screen time. This indicates a lack of consensus of the outcome of the study variables between authors. However, unlike the study by Wachira et al. (2018), the present study grouped time into weekly values to establish a more comprehensive outlook on the relationship between screen time and BMI.

Research Question 2

The second research question was "Does sedentariness moderate the relationship between screen time on the diverse social media and an individual's BMI?" The corresponding null hypothesis stated that sedentariness does not significantly moderate the relationship between social media screen time and an individual's BMI. To further extend the findings by Biddle et al. (2017), which suggested that interlinkages between BMI and screen time have been proven more consistently than interlinkages between BMI and sedentary behavior, the current study's findings indicate that sedentary lifestyles do not moderate the relationship between screen time and BMI. This reinforces the findings by Chow (2017), Mielke et al. (2017), and Wachira et al. (2018) that for some individuals, the avoidance of screen time may in fact be attributed to more sedentary time spent attending school or working at a desk. In other words, a high BMI is not necessarily triggered by a sedentary lifestyle resulting from excessive screen time, because a sedentary lifestyle can also occur due to a large assortment of factors.

Additional Findings

A Shapiro-Wilk normality test for predictor variables measuring the time spent on different types of social media posted a test coefficient of <0.001 (see Table 2), indicating evidence contrary to the test null hypothesis. Therefore, the null supposition that the test population was normally distributed was rejected. This absence of normality can be attributed to the small sample size being tested. Having established that the tested data were not normally distributed, a nonparametric Spearman's Rho's analysis was performed on the variables. As evidenced in Table 3, results revealed that whereas a correlation does not exist between BMI and social media screen time, sedentary behavior moderately positively correlated with time spent on different types of social media. Particularly, these social media types were image sites ($p < .05$), followed by discussion and video sites ($r(133) > .2$, $p < .01$). In other words, as much as BMI cannot be linked to social media screen time, young adults who spent more time on discussion and video sites were most likely to be associated with sedentary lifestyles, compared to those who only used networking sites.

The absence of significant findings in the second research question did not necessarily imply a confirmation of the null hypothesis because notably, a useful contribution of this study to existing literature is linked to the demographic factor of race. This modification involved sampling the participants by their ethnic origin. The five different races assessed by way of pairwise comparison were White, Asian, African American, American Indian and Pacific Islander, in that order. When an additional analysis was conducted to interrogate the relationship between the demographic variable of ethnic origin and the criterion variable of sedentary behavior, the results revealed that the White ethnic group had the lowest median time associated with sedentary behavior (Median = .93), while American Indians had the highest average median time (Median = 1.89). Rather than using the mean, the median was selected because based on the Shapiro-Wilk normality test, the data are not normally distributed. However, it is important to note that the American Indian race represented a comparatively small sample size in the median outcome.

Procedurally, the post hoc pairwise comparison test—upon adjustment by the Bonferroni correction for multiple tests—revealed that the differences in sedentary behavior among the ethnic groups was significant only between the Asian and African American groups. Put a different way, there was a significant difference between the median sedentary behavior scores of the Asian and African American groups. This finding provided further clarification to the results of Compernolle et al. (2016), who compared sedentary behavior and health among women living in low-income neighborhoods. Based on demographic factors such as employment status, birth country, and education level as mediated by screen time (Compernolle et al., 2016), there are differences between Asians and African American young adults, with Asians engaging in significantly less sedentary behaviors than African Americans.

Findings in the Context of the Theoretical Framework

Rosenstock's (1974) HBM is applied to make sense of individual's attitudes and beliefs in deciphering people's decisions to improve, change or adapt their health behaviors . The supposition adapted in this study was that based on research findings of the HBM, many young adolescents with high BMI circumvent opportunities for in-person socialization by preferring frequent social media use and sedentary behaviors, owing to concerns about their peers' perceptions and bias based on their weight. This study's hypotheses were drawn from research by Puhl and Brownell (2003), who established that youth are more likely to strengthen the stigma associated with being overweight by ostracizing peers in conformity with their weight, leading their overweight peers to further seclude themselves socially by engaging in sedentary and screen time activities. The results on differences in sedentary behavior scores among races in this present study support the findings of Melkevik et al. (2015) that individuals with sedentary lifestyle tend to more frequently engage in nonphysical activity, of which media consumption plays a part.

Summary

In summary, despite the lack of consensus by authors on BMI, social media screen time, and sedentary behavior, the present research findings have done more to both confirm and extend existing previous literature. In terms of population characteristics, previous researchers have focused primarily on children and adolescents (i.e., aged 10 to 17 years) as an intended demographic for assessment of BMI, social media screen time, and sedentary behavior. In the current study, I specified the distinctly underrepresented population of young adults aged 18 to 25 years. The assessment instrument used was a survey-based on the theoretical framework of Rosenstock's (1974) HMB, which focused on individuals' beliefs and perceptions about health, which lead to lifestyle changes and improvements. The online survey comprised the SBQ, additional questions about BMI, social media screen time, and participant demographics. I anticipated unpredictable results due to the limited use of HBM-based research on the social media behaviors of young adults. A qualitative research approach was not applied for this inquiry because smaller sample size and more complex data collection logistics are a barrier to transferability of results (see Leavy, 2017). In both research questions, a *p*-value greater than .05 indicates that even though the results failed to reject the null hypothesis, the results data are consistent with previous literature.

Limitations of the Study

This study was delimited to the predictor variable of BMI and the criterion variables of Internet community and sedentary behavior in young adults within the United States aged 18 to 25 years old, as a population distinct from adolescents aged 10 to 17 years old (Dietz, 2017). Participants representing all health beliefs, BMIs, social media activity levels, and levels of sedentary behavior were admitted to the present study to ensure a robust demographic.

Having established that at least 86% of Americans have Internet access (Greenwood et al., 2016), an initial potential study limitation is that participants from regions within the United States with poor Internet connectivity are likely to be underrepresented. Arguably, those individuals with limited Internet access would unlikely volunteer to participate in a study on BMI, social media screen time, and sedentary behavior. Nonetheless, it may also be argued that the larger majority of study participants are those who are actually linked to Internet connectivity; accordingly, the scope of this study still does capture a significant population.

Secondly, the disposition of the data collected in the study was self-reported, presenting a limitation where participants' responses about their BMI, social media screen time, and sedentary behavior could have been exaggerated or an inaccurate representation of their reality. To minimize the threat of internal validity, which if unchecked, would underrate the approximate truth about inferences regarding cause-effect relationships (O'Dwyer & Bernauer, 2016), a 1-week time limit to complete the survey was imposed on respondents. This effectively eliminated legitimacy threats of design contamination, history, and maturation. Further, the volunteers who took up the survey were free to stop responding at any time. This meant that I could safely assume that participants who completed the survey were willing to honestly provide information on their screen time and sedentary behavior. The internal legitimacy of participants BMI data was verified by comparing the respondent values to the national indices for BMI as a benchmark.

Thirdly, the restriction of data collection to participants in the United States denies this research a transnational frame of mind, suggesting that the research findings are not generalizable to young adults across the world, whose experiences with BMI, social media screen time, and sedentary behaviors may be motivated by different factors based on where they live. For this reason, the threat of external validity fails to apply to this research as the outcome of the study are not interpolated in a larger population (O'Dwyer & Bernauer, 2016). When probing whether the research setting will hold if done in a different setting (Tharenou et al., 2007), it is apparent that the findings of this study are only limited to those aged 18 to 25 years and living in the United States.

When considering the limitations that potentially arise owing to the study design, a review of the instruments used to collect data confirms the application of the SBQ and a self-developed questionnaire consisting of BMI, social media screen time, and demographic questions. The reliability and legitimacy of the SBQ is evidenced in its previous application as a measure to test nine different behaviors in children (Norman et al., 2005). Further, Rosenberg et al. (2010) reported that their revised SBQ has moderate to excellent reliability for weekdays (Cronbach's alpha of .64 to .90) and weekends (Cronbach's alpha of .51 to .93). Accordingly, in the present research, the SBQ was modified suit the young adult intended demographic instead of children.

The second three-part questionnaire comprised the BMI part with two questions on height and weight parameters only. The screen time comprised questions regarding how much screen time an individual spends on social media networking sites, image-sharing sites, discussion sites, and video-hosting sites. Nine choices were provided which mimicked those of the SBQ, without a distinction between weekday and weekends. The demographic parameter contained four questions about respondents' gender, age, race, and highest educational attainment, with a reliability coefficient computed for all the scale items.

A study problem which arose during implementation was a low sample size, which was evidenced by the nonexistence of extreme outliers in the data when assumption tests were conducted. Random sampling using SPSS was used to select young adults in the United States and accordingly obtain the required sample size. The selection criteria for the sample were being aged 18 to 25 years old, being fluent in English language, and living in the United States. Typically, a larger statistical distribution, spanning an intended demographic of young adults across different regions, would make it easier to identify any outliers in the dataset while minimizing the margin of error. For this inquiry, the residual scatter plot (see Figure 3) indicated homogeneity of variance and criterion variables.

Recommendations

Owing to the delimiting research setting of 18- to 25-year-old individuals in the United States, it is principally recommended that forthcoming study should expand the intended demographic to compare BMIs, social media screen time, and sedentary behavior among young adults living in other regions of the world. A larger statistical distribution would advantageously provide more precise mean values, offer smaller margin of error, and enable the identification of outliers that could potentially skew the data in a smaller sample size that is restricted to one region only.

Falbe et al. (2017) made a case for different forms of screen time and BMI when controlling for gender as the demographic, revealing that online TV, TV viewed on hand-held gadgets, and the sum of non-broadcaster TV viewing time by women in general was associated with higher BMI. Accordingly, a second recommendation is that future researchers can extend these findings by comparing the interchange between screen time and BMI for male and female young adults. A comparison between how the genders respond to these parameters in addition to psychosocial variables could shed more light on their unique behavioral patterns.

Thirdly, I recommend that environmental factors other than social media screen time and sedentary behavior be potentially correlated with an individual's BMI, because the current findings have established that a statistically significant relationship does not exist between these variables. Further, for the study population, sedentary behavior does not moderate the relationship between an individual's BMI and social media screen time. This recommendation is also supported by a 2019 research among a sample of 198 primary school students, which found that high levels of sedentary time were independent of, and not closely associated with, high levels of screen time (Hoffmann et al., 2019).

Finally, it is recommended that future studies attempt a mixed-methods approach to assessing individual's BMI, social media screen time, and sedentary behavior. Combining a qualitative approach with quantitative methods could help to elicit individual's responses as pertains to their own unique experiences with BMI, social media screen time, and sedentary behavior. This will upgrade the study to more relatable, by highlighting the lived experiences of real people, in addition to the statistics. In this way, based on Rosenstock's (1974) HBM, the changing attitudes, beliefs, and perceptions of individuals towards improving their health lifestyles can be assessed through content analysis of information generated first-hand from responses by the participants. This can be implemented through focused interviews in an open-minded setting which flexibly adapts to the human experience.

In summarizing these recommendations, given the conflicting nature of previous literature reviewed, where some researchers found evidence in support of a significant relationship between screen time and BMI (Bickham et al., 2013; Falbe et al., 2017), while others did not (Wachira et al., 2018), the expectations for this inquiry were unpredictable. It is safe to conclude that an individual's the degree to which BMI impacts the individual's interactions with others is subjective. Different individuals are exposed to different sets of circumstances including demographics and socio-economic or work-related factors, which impact differently on their BMI. It is, therefore, not logical to generalize young U.S. adults' BMI outcomes to social media screen time and sedentary lifestyles.

Implications

The purpose of this study was to question scholars' current assumptions about how sedentary behavior moderates the relationship between social media screen time and BMI among young adults in the United States. This subsection explores the positive social change implications of the study findings in relation to theory, research, and practice.

The positive social change implications of this study on individuals' beliefs and perceptions about health and well-being, based on the theoretical framework of the HBM, will serve to destigmatize overweight or obese persons in the United States, who are often blamed for their high BMI (Puhl & Brownell, 2003). With common assumptions that obesity has to do with excessive social media screen time on the part of the individual, the findings of this study established that there is no statistically significant relationship between an individual's BMI and their social media screen time. In other words, because there are other varied factors that contribute to high BMI, this present research highlights the need for exploration of early preventive lifestyle changes for young adults to circumvent detrimental health effects and improve the quality of life.

The positive social change implication of this research on policy is the credibility given to Rosenstock's (1974) HBM, the application of which in previous research has centered mainly on social media as a source of health information, rather than on the health implications of social media (Kite et al., 2018; Zhang et al., 2017). I highlighted in the literature review, how individuals experience the relationship between weight and quality of life is very subjective, based on demographic factors (Laxy et al., 2018). Therefore, based on these demographic realities, policymakers can be guided in how they address obesity prevention and intervention efforts when formulating legislation. Additionally, research propounds that exercise has a mediating influence on how screen time impacts certain health metrics (Chow, 2017). Accordingly, an emphasis on healthy lifestyle through regular exercise is a worthy advocacy and awareness goal for experts in governance and leadership.

The positive social change implications in practice for academic researchers are two-fold. First, the findings on differences in sedentary behavior scores among races in this study complement existing research on race as a demographic factor affecting BMI.. This allows forthcoming study to probe into the intrinsic factors unique to different ethnic groups by comparing variables of lifestyle, socio-economic status, along with beliefs and perceptions. Accordingly, such a study could further interrogate the findings of Skinner et al. (2018) as gathered from the 1999–2016 National Health and Nutrition Examination Survey results, which established that obesity rates among Asian and White children were significantly lower than those of children of other races, particularly Hispanic and African American children. Secondly, there is the potential for a future study to compare the association of BMI with social media screen time and sedentary behaviors for young adults from different regions of the world. This would introduce a global perspective to the research and accordingly the advantage of generalizability.

In this subsection, I discussed the implications of the present study by way of the changes or improvements which the findings introduce to understanding the phenomenon of individual's BMI, social media screen time and sedentary behavior. The next subsection summarizes the study conclusions.

Conclusions

This study successfully extended the research on BMI, social media screen time, and sedentary behavior by focusing on an intended demographic in the United States that has been under-emphasized in similar previous research, which is that of young adults aged 18 to 25 years. The main research question cross examined whether relationships exist between screen time on the diverse social media and an individual's BMI. A secondary research question interrogated whether sedentariness moderates the relationship between social-media screen time and an individual's BMI. The findings imply that overall, the variables of social-media screen time and sedentary behavior in this population have minimal to no effect on the prediction of BMI in an individual, meaning that these variables are independent. Nonetheless, in attempting to moderate the effect of sedentary behavior on the relationship with BMI, the findings confirmed the differences in median sedentary behavior particularly for Asian and African American ethnic groups.

The wider meaning of the research on BMI, social media screen time, and sedentary behavior is its contribution to pertinent discussions on health and wellness. Although technology has improved the quality of life in very many ways, it is impossible to ignore the detrimental effects of long-term social media screen time exposure to the health of individuals, and interpersonal relationships in the family and in society in general. Undoubtedly, there is no direct correlation between social media screen time and BMI. Accordingly, the assumption that all individuals with high BMI are necessarily sedentary or unregulated in their social media screen time is partly invalidated. For this reason, the emphasis on regular exercise, reduced social media screen time, and perpetuation of an active lifestyle applies to all ethnic groups alike.

In Chapter 5, I synthesized the study expectations and findings to give a comprehensive view of the problem that excessive social media screen time use and sedentary behavior is linked to health problems of obesity, high BMI scores and poor quality of life (Chow, 2017; Jackson & Cunningham, 2017; Twenge, Martin, et al., 2018) among young adults. In this chapter, I comprehensively interpreted the study findings, highlighted the limitations of the research, provided useful recommendations for future studies, discussed the implications of the study, and concluded the key applications of the findings in relation to the health and wellbeing of young adults in the United States. The study implications have far-reaching effects for theory, research, and practice.

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Appendix A: Sedentary Behavior Questionnaire

Choose the answer that best describe your behavior towards each of the activities outlined.

On a typical weekday, how much time do you spend (from when you wake up until you go to bed) doing the following?

1. Watching TV
    a. None
    b. 15 minutes or less
    c. 30 minutes
    d. 1 hour
    e. 2 hours
    f. 3 hours
    g. 4 hours
    h. 5 hours
    i. 6 hours or more
2. Playing computer/video games
    a. None
    b. 15 minutes or less
    c. 30 minutes
    d. 1 hour
    e. 2 hours
    f. 3 hours
    g. 4 hours
    h. 5 hours
    i. 6 hours or more
3. Sitting while listening to music
    a. None
    b. 15 minutes or less

c. 30 minutes
d. 1 hour
e. 2 hours
f. 3 hours
g. 4 hours
h. 5 hours
i. 6 hours or more

4. Sitting and talking on the phone
   a. None
   b. 15 minutes or less
   c. 30 minutes
   d. 1 hour
   e. 2 hours
   f. 3 hours
   g. 4 hours
   h. 5 hours
   i. 6 hours or more
5. Doing paperwork or office work
   a. None
   b. 15 minutes or less
   c. 30 minutes
   d. 1 hour
   e. 2 hours
   f. 3 hours
   g. 4 hours
   h. 5 hours
   i. 6 hours or more
6. Sitting and reading
   a. None
   b. 15 minutes or less
   c. 30 minutes
   d. 1 hour
   e. 2 hours

f. 3 hours
g. 4 hours
h. 5 hours
i. 6 hours or more

7. Playing a musical instrument
   a. None
   b. 15 minutes or less
   c. 30 minutes
   d. 1 hour
   e. 2 hours
   f. 3 hours
   g. 4 hours
   h. 5 hours
   i. 6 hours or more
8. Doing arts and crafts
   a. None
   b. 15 minutes or less
   c. 30 minutes
   d. 1 hour
   e. 2 hours
   f. 3 hours
   g. 4 hours
   h. 5 hours
   i. 6 hours or more
9. Driving/riding in a car, bus, or train
   a. None
   b. 15 minutes or less
   c. 30 minutes
   d. 1 hour
   e. 2 hours
   f. 3 hours
   g. 4 hours

h. 5 hours
i. 6 hours or more

On a typical weekend, how much time do you spend (from when you wake up until you go to bed) doing the following?

10. Watching TV
    a. None
    b. 15 minutes or less
    c. 30 minutes
    d. 1 hour
    e. 2 hours
    f. 3 hours
    g. 4 hours
    h. 5 hours
    i. 6 hours or more
11. Playing computer/video games
    a. None
    b. 15 minutes or less
    c. 30 minutes
    d. 1 hour
    e. 2 hours
    f. 3 hours
    g. 4 hours
    h. 5 hours
    i. 6 hours or more
12. Sitting while listening to music
    a. None
    b. 15 minutes or less
    c. 30 minutes
    d. 1 hour
    e. 2 hours

f. 3 hours
g. 4 hours
h. 5 hours
i. 6 hours or more

13. Sitting and talking on the phone

a. None
b. 15 minutes or less
c. 30 minutes
d. 1 hour
e. 2 hours
f. 3 hours
g. 4 hours
h. 5 hours
i. 6 hours or more

14. Doing paperwork or office work

a. None
b. 15 minutes or less
c. 30 minutes
d. 1 hour
e. 2 hours
f. 3 hours
g. 4 hours
h. 5 hours
i. 6 hours or more

15. Sitting and reading

a. None
b. 15 minutes or less
c. 30 minutes
d. 1 hour
e. 2 hours
f. 3 hours
g. 4 hours

h. 5 hours
i. 6 hours or more

16. Playing a musical instrument

a. None
b. 15 minutes or less
c. 30 minutes
d. 1 hour
e. 2 hours
f. 3 hours
g. 4 hours
h. 5 hours
i. 6 hours or more

17. Doing arts and crafts

a. None
b. 15 minutes or less
c. 30 minutes
d. 1 hour
e. 2 hours
f. 3 hours
g. 4 hours
h. 5 hours
i. 6 hours or more

18. Driving/riding in a car, bus, or train

a. None

b. 15 minutes or less

c. 30 minutes

d. 1 hour

e. 2 hours

f. 3 hours

g. 4 hours

h. 5 hours

i. 6 hours or more

Appendix B: Questionnaire for BMI, Screen Time, and Demographics

Part 1: BMI

1. What is your weight? _____ pounds (lbs) **or** ______kilograms (kgs)
2. What is your height? _____ feet and _____inches **or** ______centimeters (cms)

Part 2: Screen Time

3. On a typical day (either weekend or weekday), how much screen time do you spend (from when you wake up until you go to bed) on social networking sites such as Facebook, Instagram, Twitter, etc.?
    a. None
    b. 15 minutes or less
    c. 30 minutes
    d. 1 hour
    e. 2 hours
    f. 3 hours
    g. 4 hours
    h. 5 hours
    i. 6 hours or more

4. On a typical day (either weekend or weekday), how much screen time do you spend (from when you wake up until you go to bed) on image-sharing sites such as Instagram, Pinterest, etc.?

a. None
b. 15 minutes or less
c. 30 minutes
d. 1 hour
e. 2 hours
f. 3 hours
g. 4 hours
h. 5 hours
i. 6 hours or more

5. On a typical day (either weekend or weekday), how much screen time do you spend (from when you wake up until you go to bed) on discussion sites such as personal blogs, forums, etc.?
    a. None
    b. 15 minutes or less
    c. 30 minutes
    d. 1 hour
    e. 2 hours
    f. 3 hours
    g. 4 hours
    h. 5 hours
    i. 6 hours or more

6. On a typical day (either weekend or weekday), how much screen time do you spend (from when you wake up until you go to bed) on video-hosting sites such as YouTube, Vimeo, etc.?
    a. None
    b. 15 minutes or less
    c. 30 minutes
    d. 1 hour
    e. 2 hours
    f. 3 hours
    g. 4 hours
    h. 5 hours
    i. 6 hours or more

Part 3: Demographic

7. What is your gender?
    a. Male
    b. Female
8. What is your age? _____ years old
9. What is your race?
    a. American Indian or Alaska Native
    b. Asian
    c. Black or African American
    d. Native Hawaiian or Other Pacific Islander

e. White

10. What is your highest education attainment?

a. Some high school

b. High school diploma

c. Associate's degree

d. Bachelor's degree

e. Master's degree/Doctorate degree

Appendix C: Power Analysis Using G*Power

Figure C1

*Power Analysis Using G*Power*