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# Clicks, Likes, and Shares: Using the Theory of Planned Behavior, Self-efficacy, and Impression Management to Predict Digital Activism Activities

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Social media has evolved as a space for connection, advocacy, and commerce in recent years. Advocacy groups and organizations have been called to engage stakeholders on the Internet generally, and social media specifically as the pervasiveness of online presence has increased. To begin to help organizations develop this strategy this study seeks to answer the question: why do users engage in online activism via social media? To predict these online activism behaviors, this research tests six competing models of The Theory of Planned Behavior using a structural equation modeling approach. The results suggest these models, particularly by adding self-efficacy, may help organizations develop an effective social media strategy targeting stakeholders.

*Keywords: digital activism, slacktivism, self-efficacy, Theory of Planned Behavior*

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The protests of the Arab Spring in Egypt, Tunisia, the Ice Bucket Challenge, #BlackLivesMatter, #MeToo and beyond have demonstrated the incredible power of the Internet as a space for activism, coalition-building, and voice. The power and effectiveness of social media campaigns exert pressure on other organizations, particularly nonprofit organizations, and grassroots social movements to leverage social media in pursuit of their missions (Kumar & Thapa, 2015). The combination of expansive reach, low cost, and popularity among similar organizations has resulted in a ubiquitous social media presence (Joyce, 2010).

Nonprofit organizations, operating in dynamic environments, serving multiple bottom lines, and multiple stakeholders are increasingly using the Internet and social media to pursue their missions (McCambridge, 2017). As the popularity and pervasiveness of social media have expanded, so has the mandate for nonprofit organizations to utilize it (Tandon, 2014). More specifically, many have called on nonprofit organizations to more effectively use social media to engage the millennial population (Paulin et al., 2014) as existing nonprofit activists, volunteers, and donors age (Crosby, 2015).

Nonprofit organizations are under pressure to use social media and engage the millennial population, but many organizations lack a clear strategy to accomplish these mandates (Karch, 2016; Macnamara & Zerfass, 2012). Non-strategic social media usage can result in untapped potential or, in some cases, negative consequences for the organization (Malthouse et al., 2013). Setting a strategy based on empirical research will allow organizations to more efficiently and effectively deploy resources This research begins to explore why millennial individuals engage online in recognition that individual behavior has a tremendous impact on organizational outcomes. An essential component of strategy formation is understanding how and why people engage the target behavior (Smith, 2009). Without research to understand how and why millennials engage online, organizations are left without a fundamental element of strategy formation. This study seeks to begin to answer is what are the psychological foundations that motivate individuals in the millennial population to engage in online activism behaviors? To begin to answer the research question, six competing models of the Theory of Planned Behavior (TPB) will be tested for their ability to predict an individual's online activism behaviors.

## LITERATURE REVIEW

Academic research on this topic has focused on the outcomes of social media campaigns for nonprofit organizations, evaluation of message strategies, or critiquing these campaigns as slacktivism. Slacktivism has been conceptualized as "low-cost and low risk digital practices" such as signing petitions, "liking" a Facebook page, or re-tweeting a tweet on Twitter (Shumann & Klein, 2015, p. 308), and token displays of support online without intention or willingness to put forth significant effort in pursuit of social change (Kristofferson et al., 2013).

Examples of, so-termed 'slacktivism,' are extensive. One of the first 'slacktivism' campaigns was the yellow Livestrong bracelet supporting Lance Armstrong's Livestrong charity. More recently, colored ribbons and bracelets have been used for causes ranging from breast cancer to Alzheimer's disease. The reach of these campaigns is impressive. Millions of people around the world viewed, participated in, and shared the ALS Ice Bucket challenge in the summer of 2014, and millions of Facebook users have changed their profile pictures to show solidarity for marriage equality, for Paris in the aftermath of terrorist attacks and to support Black voices on social media platforms. These campaigns exemplify slacktivism according to some who define it as token support for a cause without intention to put forth additional effort (Kristofferson et al., 2013). Much of the academic literature on slacktivism frames these activities as driven by impression management, laziness, and social desirability (White & Peloza, 2009; Bal et al., 2013). Slacktivism can be defined as token displays of support for a cause, frequently, though not exclusively, done in virtual spaces without the intention or willingness to put forth significant effort in pursuit of social change (Kristofferson et al., 2013). Slacktivism can take the form of wearing a ribbon or wristband, "liking" or "sharing" a post on Facebook, or retweeting on Twitter. In the existing research slacktivism is positioned in contrast to traditional forms of activism such as volunteering, staging a sit-in, donating money, or joining a campaign. Kristofferson et al. (2013) argue the primary differentiation between slacktivism and traditional activism hinges on the type of support behaviors offer a social cause:

> "We refer to these types of behaviors as *token support* because they allow consumers to affiliate with a cause in ways that show their support to themselves or others with little associated effort or cost. We contrast token support with *meaningful support*, which we define as consumer contributions that require a significant cost, effort, or behavior change in ways that make *tangible contributions* to the cause." (p. 1150)

However, emerging research provides evidence that minimizing the impact of this form of activism may be shortsighted. Additionally, some research has indicated that digital activism is often part of a broader range of activities to support social causes (Center for Social Impact Communication, 2011). From this burgeoning field of research we can deduce that digital activism is indeed impactful – likely more activism than slacktivism – and digital activism tends to be part of a broader set of activities in pursuit of social causes.

Slacktivism, as conceptualized above, centers on the lack of tangible contributions or meaningful support, but this seems inconsistent with one of the outcomes of one of the most visible "slacktivist" campaigns in the last two decades – KONY 2012. The KONY 2012 campaign raised millions of dollars, achieved the stated goal to make Joseph Kony famous, and contributed to the United States sending soldiers to assist in the hunt for Kony in central Africa (Chandrasekaran, 2013). The ALS Ice Bucket Challenge also raised millions of dollars and increased the number of volunteers engaged with ALS (ALS Association, 2014). More recently, hashtags have resulted in massive social movements and protests. Indeed, one might expect that "slacktivists" are willing and engaged beyond digital platforms. As a result, this form of activism is better termed digital activism than slacktivism.

Digital activism is a form of activism that occurs, generally speaking, in an online environment. Joyce (2010) describes the nature of digital activism as concerned with campaign activities (for social change), characterized by "speed, reliability, scale, and low cost … that enable the great scope and reach of contemporary activism" (p. viii). Digital activism is using digital technologies and networks in pursuit of these campaign activities. The scope of these activities allows for access to expansive, even perhaps boundary-less, social connections and networks while also facilitating activism that is not subjected to traditional power hierarchies (Joyce, 2010). The unfettered nature of social networks and the digital space can facilitate an increased voice for those silenced by traditional forms of political engagement and activism (Murphy, 2015). The conceptualization of digital activism in this research is social media activity to "raise awareness, produce change, or grant satisfaction to the person engaged in the activity" (Rotman et al., 2011 p. 821). Setting aside the, perhaps false, delineations between meaningful and non-meaningful support, it is important to better understand the nature of "digital activism" and ascertain how engaging in these behaviors may impact further social engagement and other attitudes.

It seems clear that engaging in digital activism, similar to all forms of activism, is at least partially motivated by impression management and is attractive because of the relative little effort required. Neutralizing the initial sting of this critique Budish (2012) argues,

> "the problem with the slacktivism critique is that it is unsurprising that more people participate in easier activities than harder ones. That fact alone does not tell us whether Facebook and other easy forms of participation are cannibalizing

individuals who would otherwise contribute in more tangible and meaningful ways." (p. 752)

Present in many critiques of slacktivism is an implicit and sometimes explicit assumption that it represents a fixed space in which a slacktivist will remain. This assumption is particularly troubling given the evidence refuting that claim. The Center for Social Impact Communication (2011) at Georgetown University sought to better understand the predictive power and impact of slacktivism on future social cause engagement. The findings provide empirical evidence in stark contrast to armchair critiques. Their study, termed The Dynamics of Cause Engagement, found that "slacktivists" participate in twice as many activities, are twice as likely to volunteer their time, four times as likely to contact a political representative and equally as likely to donate money when compared to "non-slacktivists" (Center for Social Impact Communication, 2011). Lee and Hsieh (2013) found that, after controlling for demographic variables, individuals who engaged in digital activism were more likely to write to their government, and Shulman and Klein (2015) found that slacktivists were more likely to attend a discussion or sign a petition, but were reluctant to engage in more demanding offline activities. That is, social media activism is often done in addition to other forms of activism. So, important research questions and areas for exploration center on how organizations can motivate users to engage in their advocacy campaigns.

## Self-Efficacy

Self-efficacy is "one's beliefs in one's capability to organize and execute the courses of action required to manage prospective situations" (Bandura, 1997, p. 2). Put more simply, self-efficacy is one's self-beliefs about their ability to succeed in a particular setting or behavior (Bandura, 1977, 1986, 1997; Eroglu & Unlu, 2015; Pingree, 2011). Importantly, self-efficacy is not an overarching personality construct such as confidence or self-esteem. Instead, as Barry and Finney (2009) note, "it is domain specific, that is, self-efficacy judgements are specific to certain tasks in certain situations" (p. 197-198). Narrowing the target behavior in such a way is consistent with measuring self-efficacy beliefs, as more specific measures have been demonstrated to be more predictive (Barrey & Finney, 2009).

In developing self-efficacy related to a particular target behavior one may use any combination of the following information sources: enactive attainment, vicarious experience, verbal persuasion, and physiological state (Bandura, 1986, 1997). It is important to note that self-efficacy is formed iteratively and constructed through performance, memory, and environment. First, enactive attainment, often called mastery experiences (Pajares & Schunk, 2001; Reubsaet et al., 2003) is the most important source of efficacy behavior. Enactive attainment is the direct experience one has with a target behavior and subsequently their appraisal of their performance related to that behavior (Bandura, 1986). Mastery experiences elevate self-efficacy as the more positive the appraisal of the mastery experience the higher the self-efficacy. This axiom of the theory has been demonstrated in a variety of research from organ donation (Reubsaet et al., 2003) to cross-cultural efficacy (Liang & Prince, 2008). Second, vicarious experiences elevate self-efficacy when one witnesses a peer master the target behavior (Bandura, 1997). This source of self-efficacy has several caveats from empirical research. First, if one witnesses a peer fail at a target behavior one's self-efficacy for that target behavior will decrease if one evaluates their own abilities as similar. Additionally, this source of efficacy is particularly important to individuals with little experience with the target behavior (Bandura, 1986).

Third, verbal persuasion and social influence can increase self-efficacy. Motivation is one of the strongest outcomes associated with self-efficacy (Bandura, 1986, 1997; Pajares, 2002). Social influence, though not as effective as the two previous sources of efficacy (Pajares & Schunk, 2001) is most effective when an individual is predisposed to believe they can successfully engage in the target behavior (Bandura, 1986). Finally, one's physiological state can influence one's self-efficacy. Physiological state refers both to one's level of stress or anxiety at the thought of engaging in a target behavior and the more literal, physical aspects of a person that provide an inclination they may succeed at a particular task (Bandura, 1986, 1997). These sources of efficacy combine to provide an individual with information from which to evaluate their ability to be successful given a particular behavior. Improving self-efficacy related to digital activism may help predict the likelihood to engage in activism behaviors. Improving self-efficacy should help increase predictive effectiveness, but impression management, as previously noted, will still be an important motivator.

**Impression Management**

Often traced back to Goffman's (1955, 1959) work on Facework theory and his seminal work *The presentation of self in everyday life*, impression management is conceptualized as "the process by which individuals attempt to control the impressions others form of them" (Leary & Kowalski, 1990, p. 34). These impressions are a function of our social interaction and are driven by individual notions of ideal self. Impressions are presented through various forms of social interaction, symbolic action, and self-presentation behaviors

Goffman (1959) argued that this self-presentation or impression management behavior is done strategically to uphold a positive image. Impression management occurs in face-to-face and online contexts, particularly via social media sites such as Facebook and Twitter (Zhao et al., 2008). A body of literature is beginning to emerge investigating users' impression management tactics on social media (boyd & Ellison, 2007; Jeong & Lee, 2013; Rosenberg & Egbert, 2011; Zhao et al., 2008). Social media is a uniquely public space and, therefore, is more impactful on a how likely an individual is to accomplish their impression management goals (Rosenberg & Egbert, 2011; Leary & Kowalski, 1990). In particular Jeong and Lee (2013) investigated how users may manage their impressions by supporting social causes online.

Impression management is a common motive cited by critics of social media activism and those terming this form of activism "slacktivism" (Kristofferson et al., 2013; Lim, 2013; Budish, 2012; Morozov, 2009) who often cite it as the primary motivation for engaging in such activism. Given the immediate, selective, and public nature of social media, impression management motives are particularly relevant (Jeong & Lee, 2013; boyd & Ellison, 2007; Walther, 1996). Additionally, self-interested motives for donating to a charity, often termed warm-glow giving, (Andreoni, 1990), volunteering with a nonprofit organization (Houle et al., 2005), and supporting a cause on a social media platform (Jeong & Lee, 2013) have been documented in previous research. More specifically, the visibility of supporting a social cause on social media has been shown to influence an individual's intention to join an organization and support the cause online (Jeong & Lee, 2013; White

& Peloza, 2009). It seems evident that impression management plays an important role in motivating behavior generally and social support online, specifically. However, these studies have not examined the role impression management plays in comparison to other behavioral motivations such as self-efficacy and the psychological foundations of behavior posited by the Theory of Planned Behavior.

**The Theory of Planned Behavior**

The focus of the current study is the theory of planned behavior, which attempts to predict behavior from norms, attitudes, control, and intentions (Anderson et al., 2013). The theory of planned behavior has been studied extensively in a variety of fields including: health (Godin & Kok, 1996), pro-environmental behavior (Ho et al., 2015), philanthropy (Kinnally & Brinkerhoff, 2013), and political participation (Kelly & Breinlinger, 1995). Understanding the psychological foundations of engaging in digital activism is essential to building an evidence-based body of knowledge about virtual social cause engagement.

The theory of planned behavior (TPB) forecasts behavior by attempting to predict behavioral intention. Realizing it is difficult to predict actual behavior, Fishbein and Ajzen (1975) instead sought to predict behavioral intention, what a person plans to do, as it is a strong predictor of actual behavior (Ho et al., 2015). First, attitudes are central in predicting behavior. Attitudes are the positive or negatively valanced feelings an individual has toward an object, behavior, or person (Fishbein & Ajzen, 1975, 2010). In particularly, TPB uses specific attitudes toward specific behavior. Extensive research on attitudes has concluded that the more specific an attitude and the more specific its target (the behavior) the more predictive utility (O'Keefe, 1990). Next, subjective norms represent a person's perception of how significant others will evaluate their "performance or nonperformance of the behavior" (O'Keefe, 1990, p. 80). The approval of significant others in one's life has an important role in predicting behavioral intention. Behavioral intention is not singularly about a person's beliefs and attitudes but their own evaluation of how significant others will react to specific behaviors (Fishbein & Ajzen, 1975; 2010; Paek et al., 2012).

Finally, TPB argues perceived behavioral control also predicts behavioral intention and actual behavior (Fishbein & Ajzen, 1975). The concept of perceived control differentiates the theory of planned behavior from the theory of reasoned action. Perceived behavioral control is a person's confidence that they can and have the agency to complete a specific task or activity (Ajzen, 2002) and influences behavioral intention and actual behavior such that the more behavioral control a person perceives, the stronger their intent to engage in a particular behavior. Behavioral control is comprised of both internal and external factors (Ajzen, 2002). Internal factors include intelligence, skills, and confidence while external factors include resources and other circumstances that may prevent or allow completion of a behavior.

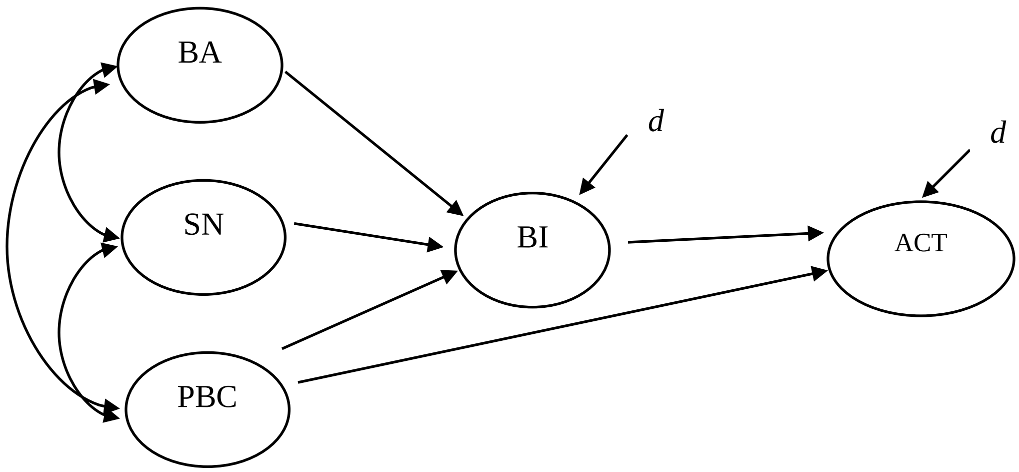
Perceived behavioral control is similar to Bandura's (1982) concept perceived self-efficacy construct. Ajzen (1991) suggested that behavioral control had both situational and specific elements. The internal factors, a person's belief in their ability to perform an activity, are similar to self-efficacy (Kraft et al., 2005; Taylor & Todd, 1995; Ajzen, 1991). In fact, some researchers (Povey et al., 2000) have argued that the concepts are so similar self-efficacy can be used as a proxy for behavioral control (ETPB) while others (Armitage et al., 1999; Terry & O'Leary, 1995) have suggested self-efficacy should be added to TPB as a predictor of both behavioral intention and actual behavior. The situational elements, termed facilitating conditions, are those factors, external to a person's perceived ability, that facilitate or hinder them from being able to engage in an activity. The three theoretical models of TPB (traditional TPB, self-efficacy added to traditional TPB, self-efficacy replacing behavioral control (ETPB)) are tested in this research. In addition to the three TPB models, the same three models including impression management as a predictor of behavior (digital and traditional activism) are also tested.

## Specification of the Models

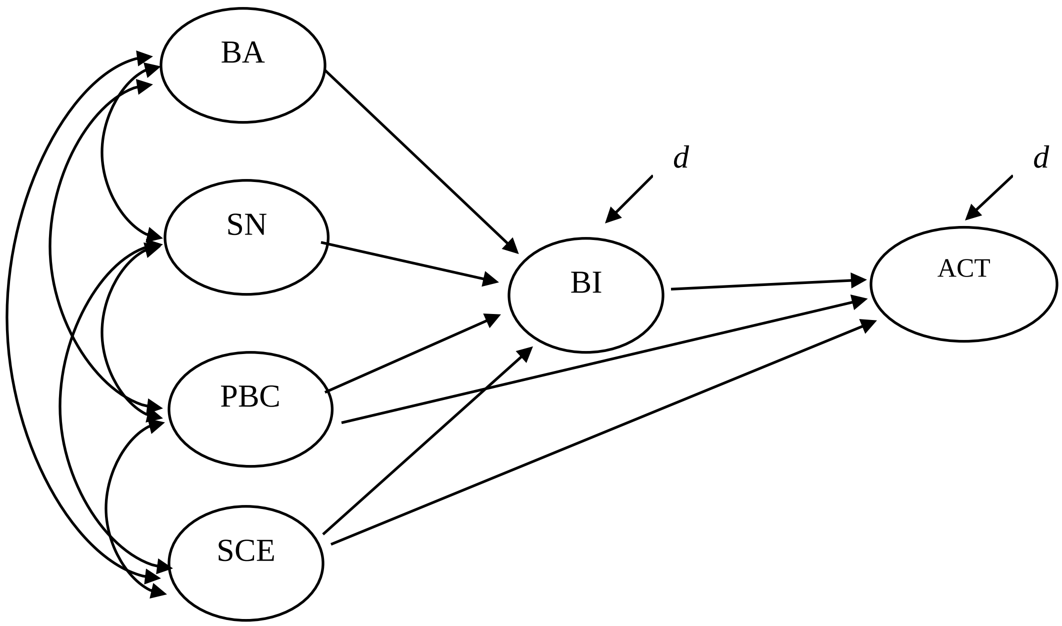
The purpose of study two is to test the six models presented in Figure 1 to rule out nonplausible models.

**Figure 1.** Competing models predicting digital & traditional activism

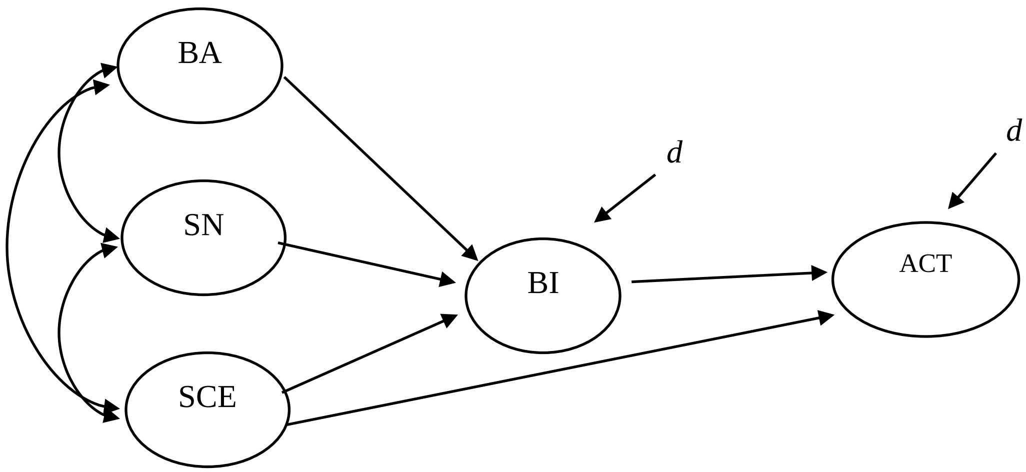
Model 1: Theory of Planned Behavior



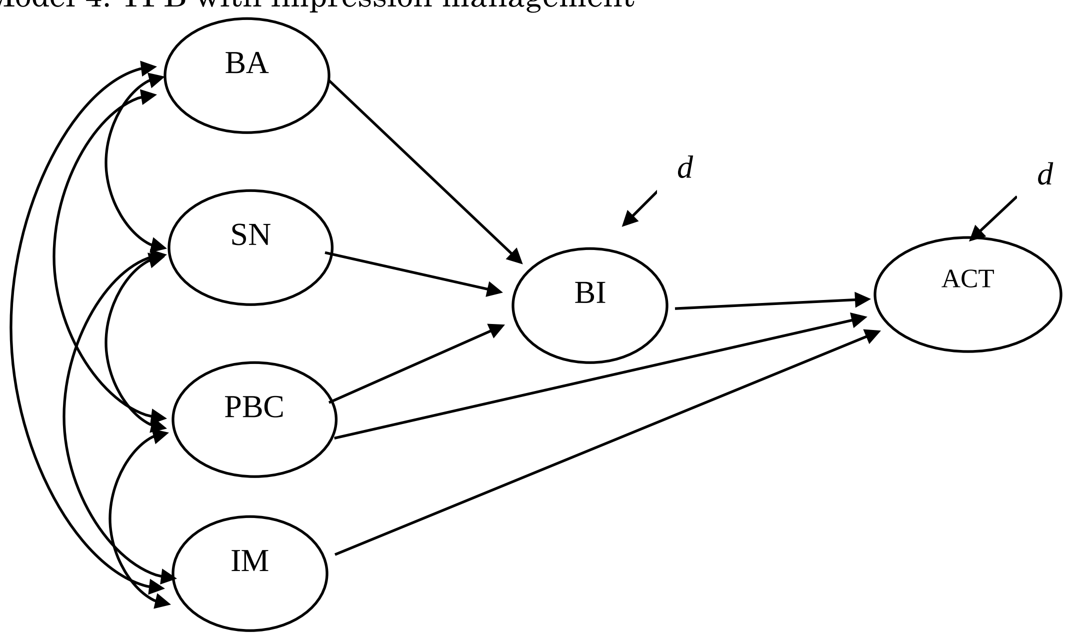

Model 2. TPB with SCE added



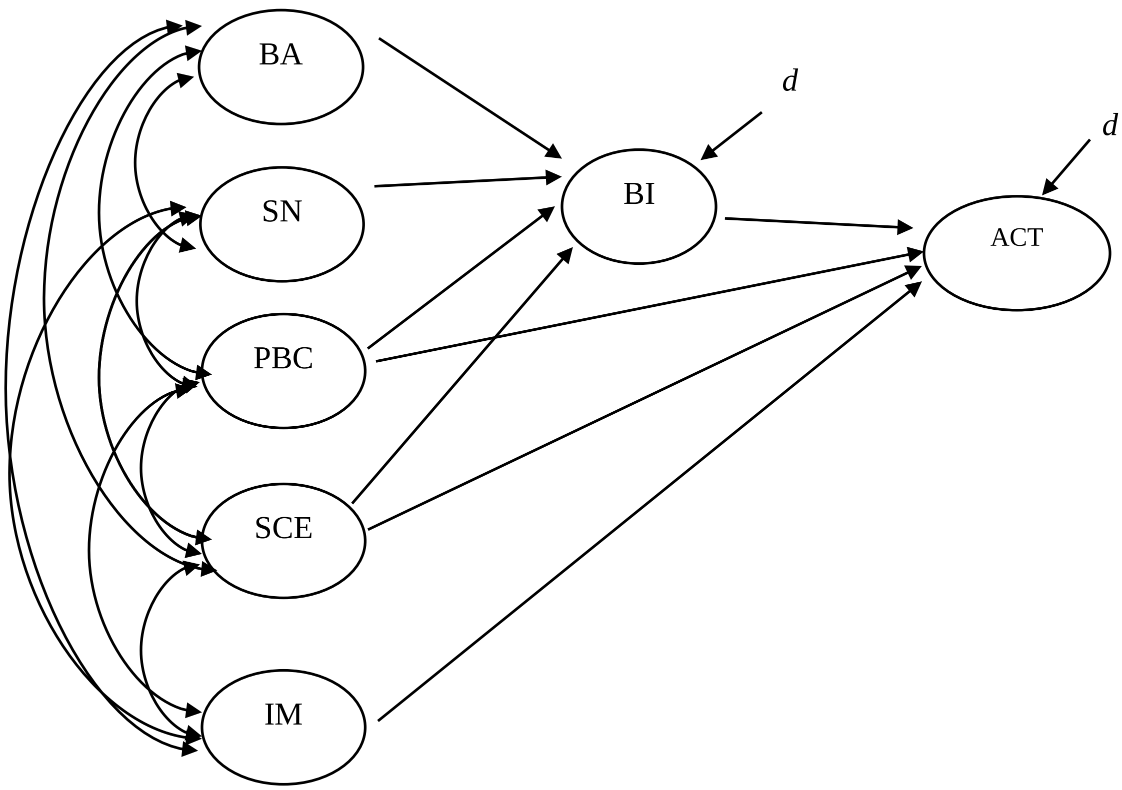
Model 3. TPB substituting SCE for Behavioral Control (ETPB)



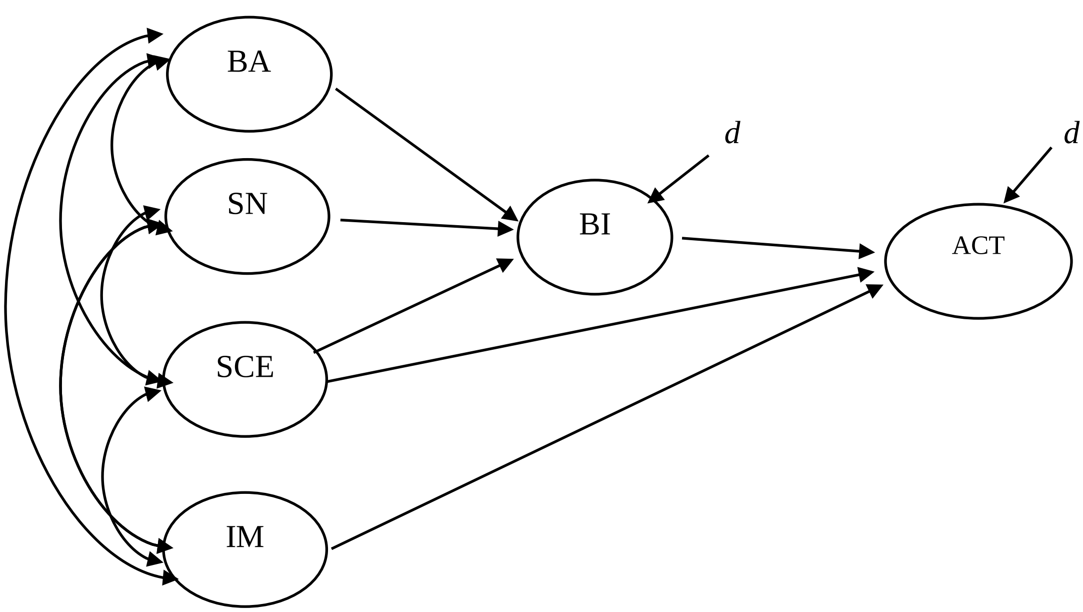

Model 4. TPB with impression management



Model 5. TPB with SCE and impression management




Model 6. TPB with SCE replacing behavioral control and impression management.




*Note: BA = Behavioral Attitudes SN = Subjective Norms PBC = Perceived Behavioral Control SCE = Social Cause Engagement Efficacy, BI = Behavioral Intention, ACT = Activism Engagement, IM = Impression Management*

***Model 1***: *3 correlations between the exogenous variables, 3 exogenous variances, 5 path coefficients, and 2 endogenous disturbance terms resulting in 2 degrees of freedom.*
***Model 2:*** *6 correlations between the exogenous variables, 4 exogenous variances, 7 path coefficients, and 2 endogenous disturbance terms resulting in 2 degrees of freedom.*
***Model 3***: *estimates the same parameters as Model 1 substituting social cause engagement efficacy for behavioral control resulting in the same 2 degrees of freedom.*
***Model 4***: *6 correlations between the exogenous variables, 4 exogenous variances, 6 path coefficients, and 2 endogenous disturbance terms resulting in 3 degrees of freedom.*
***Model 5:*** *10 correlations between the exogenous variables, 5 exogenous variances, 8 path coefficients, and 2 endogenous disturbance terms resulting in 3 degrees of freedom.*
***Model 6***: *estimates the same parameters as Model 4 substituting social cause engagement efficacy for behavioral control resulting in the same 3 degrees of freedom.*

The first model is the original conceptualization of Theory of Planned Behavior (Ajzen, 1991). This model predicts attitudes toward digital activism (BA), subjective norms about digital activism (SN), and perceived behavioral control (BC) as correlated exogenous variables with direct effects on behavioral intention. These three variables are each also predicted to indirectly effect digital activism engagement mediated by behavioral intention. In addition to the indirect effect on digital activism engagement through behavioral intention, behavioral control is also predicted to have a direct effect on digital activism engagement. Finally, behavioral intention has a direct effect on digital activism.

Other theoretical models of TPB have integrated self-efficacy to the model (Povey et al., 2000; Armitage et al., 1999; Terry & O'Leary, 1995), and Ajzen (1991) acknowledged self-efficacy was similar and complimentary to behavioral control. The measure of self-efficacy used in this study is social cause engagement efficacy. Social cause engagement efficacy has its roots in self-efficacy theory first developed by Bandura (1977, 1986). Social cause engagement efficacy is conceptualized as feelings of confidence in one's ability to engage in social cause activism (Pingree, 2011). Some scholars have added a measure of self-efficacy to the traditional model of TPB (Terry & O'Leary, 1995), Model 2 in Figure 1 represents that model. The change from Model 1 to Model 2 is the addition of self-efficacy to the traditional TPB framework such that self-efficacy is a correlated exogenous variable with direct effects on both behavioral intention and digital activism engagement and an indirect effect on digital activism engagement mediated by behavioral intention.

Finally, some researchers (Povey et al., 2000) have advocated replacing behavioral control with self-efficacy as the measures are redundant and self-efficacy represents a more effective way to predict behavior. This theory is represented by Model 3 in Figure 1. Model 3 and Model 1 are identical except that Model 3 removes behavioral control and replaces it with social cause engagement efficacy. Thus, attitudes toward digital activism, subjective norms, and social cause engagement efficacy are the correlated exogenous variables predicted to have direct effects on behavioral intention and indirect effects on digital activism engagement mediated by behavioral intention. Additionally, social cause engagement efficacy is predicted to have a direct effect on digital activism engagement.

In addition to adding social cause engagement efficacy, some critics of digital activism argue it is motivated by a desire for affiliation, self-presentation, and other selfish motives referred to as impression management (White & Peloza, 2009; Bal et al., 2013). Impression management is conceptualized as "the process by which individuals attempt to control the impressions others form of them" (Leary & Kowalski, 1990, pg. 34). Impression management theorizes that the more public an act or representation, the more motivated an individual "to manage the impressions" others will see (Jeong & Lee, 2013, pg. 440). Previous research has demonstrated impression management as an extrinsic motivation for supporting a social cause offline; however, the likelihood of impression management playing an important role in supporting social causes online is heightened due to the "malleable and selective" nature of online self-presentation (Jeong & Lee, 2013, pg. 441). This research treats impression management driven support for a social cause as a function of social trends, not as a logical response to intrinsic motivations to support a cause. Therefore, impression management will be tested as an exogenous predictor with a direct effect on behavior, but no indirect effect on behavior through behavioral intention.

As a result, the next three models add impression management as an additional correlated exogenous predictor to all of the first three models. Model 4 is the TPB framework, same as Model 1, with impression management as a correlated exogenous predictor with a direct effect on activism. Model 5 is the TPB framework with the addition of social cause engagement efficacy, same as Model 2, with impression management added as a correlated exogenous predictor with a direct effect on activism. Finally, Model 6 is the ETPB framework (social cause engagement efficacy replacing behavioral control), same as Model 3, with impression management added as a correlated exogenous predictor with a direct effect on activism.

The purpose of this study was to test the models with regard to their ability to predict online activism behaviors. This study uses a bounded sampling approach, survey research, and structural equation modeling to answer the research questions. As will be described, given the limited representativeness of the sample, conclusions must be bound to this sample and should be tested in other samples.

**Measures**

*Social cause engagement efficacy* is measure of self-efficacy applied to online and traditional activism (social cause engagement) developed for testing in this study. Social cause engagement was operationalized using a new 26-item Likert-type measure (1- strongly disagree to 7 – strongly agree). The construction of this scale follows the guidelines for creating self-efficacy scales set forth by Bandura. Self-efficacy is context specific, a measure of capability, and should not be confused with intention or outcome expectations. The scale is separated based on the context in which activism happens. The first 13 items (generic) do not specify an online environment while the second 13 items (online) are the same, but they ask the respondent to answer the questions about their confidence to engage in these activities online. Thus, the two 13-item scales which combine to form the 26-item total scale are identical, with the exception of the description of where the activism behaviors occur. In the generic scale, the context is not specified, it is left generic; while in the online scale, the participants are directly instructed to answer the questions based on their confidence in their ability to complete the behaviors online. The directions ask the respondent to evaluate their confidence in their capability to effectively engage in the following behaviors. Sample items include, influencing the decisions of others, persuade others, be part of a social movement, persuade others to take action to solve a problem, and enact social change.

To operationalize the process underlying the theory of planned behavior a number of subscales will be used: attitudes toward behavior, subjective norms, perceived behavioral control, behavioral intention, and digital activism engagement. The scales to be used in this research are based on previous operationalizations of TPB used by Muzaffar et al. (2014) to test behavioral intention in reducing type 2 diabetes risk behaviors. The scale will be modified to reflect digital activism behaviors. They reported strong alpha reliability scores for each of the measures of theory of TPB ranging from .74 -

.87 consistent with previous research using TPB measures (Lautenschlager & Smith, 2007; Rhodes et al., 2006). The subject of the scales will be changed from health behaviors to questions pertaining to digital activism consistent with a previous application of this scale to digital activism.

*Behavioral attitudes* will be operationalized using seven likert items asking participants about their attitudes toward engaging in digital activism. Sample items include: "For me, sharing advocacy messages is important" and "People should not use social media for activism." *Subjective norms* will be operationalized using nine Likert items (1-strongly disagree to 7 – strongly agree) asking the participant to describe how their friends would react to them engaging in various forms of digital activism. *Perceived behavioral control* is an indication of how much a participant perceives she/he has control over their ability to engage in a particular behavior uninhibited. In this study, it will be operationalized with 12 Likert items (1-strongly disagree to 7 – strongly agree) asking participants about their perceived control over target behaviors such as persuading leaders, joining an advocacy organization, and posting messages on social media. *Behavioral intention* is a measure of how a person intends to behave and what specific behaviors they intend to engage in. In this study, behavioral intention will be operationalized using ten Likert items (1 – Definitely will not to 5-Definitely Will) asking participants to indicate their intention to engage in activism behavior.

*Impression management* will be operationalized using seventeen Likert items (1-strongly disagree to 5 – strongly agree) asking respondents how they present themselves in online environments. The measure is a modified version of Michikyan et al.'s (2014) Self Presentation on Facebook Questionnaire (SPFBQ). This questionnaire asks respondents questions specifically about Facebook, but will be modified such that "Facebook" will be replaced with "social media" in the questions. The questionnaire has five factors relating to presentation of different aspects of self online: real self, ideal self, false self-deception, exploration, and compare/impress.

*Social cause engagement efficacy* is the 12-item online social cause engagement efficacy measure of self-efficacy described in Study 1. *Activism Engagement* will be operationalized by the frequency (1-Never to 5 – Very Frequently) with which a person engages in both digital activism activities such as liking, favoriting, or sharing social media messages, and "traditional" activism activities such as joining, donating to, or volunteering with a social cause organization.

**Data Collection Procedures and Participants**

A large (1,366) sample of students from a large southeastern university was recruited using a cloud-based participant management program called SONA Systems. Participation in "research" is a required component of some of the courses and will be offered as extra credit in others. The SONA system allows students to select a variety of research studies to complete and receive course credit for without collecting individual identity markers within the survey. Students will use the online SONA interface to click on a survey they wish to take and will then be directed to a Qualtrics survey to complete.

Students in the introductory communication course are primarily first-year students with some second-year and transfer students. The population of this university is heavily Caucasian and middle to upper class. The descriptive statistics were indicative of the population from which this sample was taken. The sample consisted of mostly white (80%), middle and upper class (89%), women (71%), who are mostly freshman (95%), and 18-19 years of age (97%). Though this sample is limited in its ability to generalize to the broader millennial population, it is one of the only study's to investigate and model psychological motivations for engaging in online activism behavior with a millennial sample. As previously detailed, nonprofits have sought increased engagement with millennials, particularly via social media (Pyser, 2014; Briones et al., 2013; Sisco & McCorkindale, 2013; Williams, et al., 2012)

To conduct the path analysis a process called single-item composites will be used. Single-item composites allow the research to, using Cronbach's alpha, model unreliable portions of variance leaving only the reliable portion left to covary with other constructs in the model. This process is described below. The practice of summing and averaging the scores for each of the scales is consistent with practice using these instruments in previous research as detailed above. The process of using single-item composites for latent constructs allows the researcher to model measurement error associated with the composites, and yields less biased path coefficients (Cole & Preacher, 2014; DeShon, 1998). Using the calculated Cronbach's coefficient alpha for each composite, the proportion of variance due to measurement error was calculated ($1-\alpha$). The resulting value was multiplied by the unstandardized variance of the composite (construct scale) and set as the single-item composite's error variance leaving only the reliable portion of the construct left to relate to the other constructs in the model. Finally, the path from the construct to the singe-item composite was set to one to allow for the measurement metric of the construct to be set in the model.

## RESULTS

Data collection procedures spanned 9 months from April 2016 to December 2016 and resulted in a total of 1,617 participants, 1,366 of which had no missing data. Participants were deleted listwise so that the 1,366 participants in the sample all had complete data. SPSS 24.0 was used to clean data, calculate mean scale scores, reliabilities, intercorrelations, descriptive statistics, and check for univariate and multivariate normality. Range checks were completed to clean the data and items that required reverse coding were reverse coded.

Reliability analysis was also conducted for each scale in SPSS to determine Cronbach's alpha for the scales used in the models. Most of the scales yielded strong reliability, subjective norms ($M = 4.48$, $\alpha = .93$), behavioral control ($M = 5.14$, $\alpha = .79$), behavioral intention ($M = 3.03$, $\alpha = .88$), online activism ($M = 2.59$, $\alpha = .87$), and efficacy ($M = 4.47$, $\alpha = .94$). Alpha scores for the behavioral attitudes ($M = 4.71$, $\alpha = .61$) and impression management ($M = 2.62$, $\alpha = .67$) scales were below the .70 threshold widely acceptable as sufficient reliability.

After preliminary data analysis in SPSS, the raw mean scores for each participant were read into LISREL 9.2 and covariance and asymptotic covariance matrices were generated. As outlined below, the asymptotic covariance matrix is necessary for structural equation modeling techniques when data is nonnormal.

### Model Estimation and Fit Indices

To determine the appropriate estimation procedure and fit indices to use in the path analysis, data were screened for normality using SPSS. Structural equation modeling techniques are sensitive to both univariate skew and kurtosis and multivariate skew and kurtosis. Some fit indices require modification if data is nonnormal, thus data must be screened for univariate and multivariate normality before fit indices and estimation methods can be selected. First, data were screened for univariate skewness and kurtosis. The results indicated no univariate skewness or kurtosis as values were all below |3| or |8|, respectively (Finney & DiStefano, 2013). However, because estimation methods assume both univariate and multivariate normality, it is also important to demonstrate multivariate normality as well. To test for multivariate normality Mardia's test was performed using the DeCarlo (1997) macro. The result of Mardia's test was 21.32, above the cutoff of 3 suggested by Bentler and Wu (2003), indicating the data for this research was nonnormal.

Maximum Likelihood (ML) is sensitive to model misspecification, appropriate for the sample size, and adjustable for nonnormal data; thus it was used to estimate the models in this research (Olsson et al., 2000; Olsson et al., 1999; Hu & Bentler, 1998). When data are nonnormal, as in this research, the standard errors and fit indices need to be adjusted for nonnormality using the Satorra Bentler adjustment (Hu & Bentler, 1998). As a result, the models were estimated using maximum likelihood with the Satorra Bentler adjustment. To analyze overall model data fit, Hu and Bentler (1998, 1999) recommend a complimentary two fit-index presentation strategy in addition to the $\chi^2$ fit index, and recommend Standardized Root Mean Squared Residuals (SRMR) should always be reported. The two-index strategy should reflect overall model data fit using a global fit index and an incremental fit index to compare the tested model with a null model in which none of the constructs are correlated. Additionally, the selected fit indices should complement on their sensitivity to simple and complex model misspecification. Simple model misspecification is associated with misfit due to factor (construct) correlations while complex model misspecification is associated with misfit due to path coefficients (Hu & Bentler, 1998; 1999). This strategy provides information about how the tested model compares to a perfectly fitting and a null model (Hu & Bentler, 1999).

The most basic fit index is Chi Square ($\chi^2$). $\chi^2$ is a measure of perfect fit with higher values indicating poorer fit. If a model fits the data well the resulting $\chi^2$ value should approximate the degrees of freedom in the model. A significant $\chi^2$ test indicates the model does not fit the data well. However, $\chi^{2\text{ is}}$ very sensitive to sample size overly rejecting plausible models and assessing approximate fit instead of perfect fit is a more realistic goal in social scientific research (Hu & Bentler, 1998, 1999; Marsh et al., 2004). However, large $\chi^2$ do indicate poor model data fit.

Three additional fit indices will be used in this research, SRMR, Root Mean Square Error of Approximation (RMSEA), and Comparative Fit Index (CFI). SRMR and RMSEA are both global fit indices, comparing the theoretical model to a model with perfect fit, while CFI is an incremental fit index, comparing the theoretical model to a null model in which none of the constructs are correlated. The SRMR is very sensitive to simple model misspecification due to factor correlations and moderately sensitive to path coefficient misspecification. Hu and Bentler (1998) recommend always reporting the SRMR, which ranges from 0-1, and recommend a cutoff of .08 with higher values indicating poorer fit (Hu & Bentler, 1999). RMSEA is very sensitive to complex model misspecification due to path coefficients making it complimentary to SRMR (Hu & Bentler, 1998); however, RMSEA can overly reject correct models when sample sizes are small (Rigdon, 1996). Another strength of RMSEA, is it isolates misfit due to model misspecification by adjusting for sampling error using the noncentrality parameter based on degrees of freedom. That is, RMSEA provides a measure of misfit per degree of freedom making it sensitive to parsimonious models. RMSEA also ranges from 0-1 with higher values indicating poorer fit. Hu and Bentler (1999) recommend a cutoff of .06 while Browne and Cudeck indicate values between .05 - .08 suggest close fit while values above .10 indicate poor fit. Finally, CFI is an incremental fit index that assesses fit compared to a null model. CFI is very sensitive to complex model misspeficiation and moderately sensitive to simple misspecifcation (Hu & Bentler, 1998). Values of the CFI range from 0 – 1 with higher values indicating stronger fit (Hu & Bentler, 1998), and Hu and Bentler (1999) recommend a cutoff of .95. It should be noted that Marsh et al. (2004) argued all of the cutoffs proposed by Hu and Bentler (1999) may be too strict and should be interpreted in conjunction with domain specific considerations in mind. Finally, if fit indices indicate a model is plausible the researcher will then examine covariance residuals to investigate areas of local misfit with residuals above |3| or |4| indicating local misfit (France & Finney, 2010; Bryne, 1998). Local misfit provides information on the specific paths (or missing paths) that are sources of model misfit. Analyzing covariance residuals and the variance explained in the endogenous variables represent the second step of model comparison. The goal of model analysis is to discount implausible models and test the theory represented in each of the models under investigation.

**Descriptive Statistics and Foreshadowing Results**

Descriptive statistics, correlations, and scale statistics are shown in Table 3. Respondents indicated neutral responses to most the scales and the sample had moderate levels of variability. Scores for most scales were around the scale mean. In particular, attitudes about engaging in online activism ($M = 4.71$ $SD = .93$), normative expectations from friends and family about them engaging in slacktivism ($M = 4.48$, $SD = 1.08$), their personal intentions to engage in online activism ($M = 3.03$ $SD = .86$), their impression management motives ($M = 2.62$ $SD = .40$), their efficacy to engage in online activism ($M = 4.47$ $SD = 1.12$), and the frequency with which respondents engaged in online activism ($M = 2.59$ $SD = .96$) However, students reported higher levels of behavioral control ($M = 5.14$ $SD = .94$).

**Table 3.** Intercorrelations, descriptive, and scale statistics for variables

| Variable | Attitude | Norms | Control | Intention | Activism | Efficacy | Imp Mgt. |
|---|---|---|---|---|---|---|---|
| Attitude | -- | | | | | | |
| Norms | .496** | -- | | | | | |
| Control | .451** | .412** | -- | | | | |
| Intention | .441** | .523** | .298** | -- | | | |
| Activism | .356** | .432** | .190** | .712** | -- | | |
| Efficacy | .380** | .437** | .380** | .395** | .322** | -- | |
| Imp Mgt. | -.210** | -,113** | -.232** | -0.011 | .095** | -.104** | -- |
| *Mean* | 4.71 | 4.48 | 5.14 | 3.03 | 2.59 | 4.47 | 2.62 |
| *SD* | 0.93 | 1.08 | 0.94 | 0.86 | 0.96 | 1.12 | 0.40 |
| Skew (SE = .066) | -0.04 | -0.18 | -0.26 | 0.04 | 0.34 | -0.46 | -0.33 |
| Kurtosis (SE = .132) | 0.02 | 0.72 | 0.10 | -0.25 | -0.39 | 0.54 | -0.42 |
| Cronbach's α | 0.61 | 0.93 | 0.79 | 0.88 | 0.87 | 0.94 | 0.67 |

** $p$<.01

The correlation matrix can be used to foreshadow results of the path model. While the large sample size (1,366) yielded significant correlations in terms of their $p$ values, the strength of the correlations are not all practically significance. The magnitude of the correlations will be evaluated using Cohen's (1988) conventions: .10 - .30 (weak), .30 - .50 (moderate), .50 – 1.0 (strong). As predicted, behavioral attitudes (.441) and subjective norms (.523) were significantly correlated with behavioral intention. Behavioral control

(.298) yielded a weak but nearly moderate correlation with behavioral intention and social cause engagement efficacy (.395) was also moderately correlated to intention. Finally, impression management has little to no relationship (-.011) to intention or engaging in activism (.095), and weak negative correlations with attitudes (-.210), norms (-.113), control (-.232), and efficacy (-.104). Intention, as predicted, has a strong correlation (.712) and social cause engagement efficacy (.322) was moderately correlated with engaging in activism. This indicates that, with regard to engaging in online activism, perceived control and impression management may not be as influential as intention and efficacy. Further, the strongest correlation control has is with efficacy have. This finding supports the contention by some scholars (Kraft et al., 2005; Taylor & Todd, 1995) that efficacy and behavioral control may be somewhat redundant.

**Path Analysis**

The six a priori specified models (shown in Figure 1) were estimated using Maximum Likelihood with the Satorra Bentler adjustment in LISREL 9.2 (Jöreskog & Sörbom, 2013). To conduct and interpret the path analysis results, the four fit indices were analyzed using the Hu and Bentler (1999) and Brown and Cudek's (1993) guidelines. However, it should be noted that Marsh, Hau, and Wen (2004) argued all of the cutoffs proposed by Hu and Bentler (1999) may be too strict and should be interpreted in conjunction with domain specific considerations in mind. The data in this study were analyzed by looking at the battery of fit indices used, such that models with values close to the suggested cutoffs were kept for consideration while those models with values not close to the suggested cutoff were removed from consideration. Fit indices and comparisons are shown in Table 4.

**Table 4.** Fit Indices for Competing Models (n=1,366)

| Model | $\chi^2_{\sigma\beta}$ | df | *p*-value | CFI | SRMR | RMSEA |
|---|---|---|---|---|---|---|
| 1 | 47.99 | 2 | <.001 | 0.962 | 0.036 | 0.130 |
| 2 | 17.03 | 2 | <.001 | 0.992 | 0.013 | 0.074 |
| 3 | 96.30 | 2 | <.001 | 0.923 | 0.066 | 0.186 |
| 4 | 30.40 | 3 | <.001 | 0.986 | 0.024 | 0.082 |
| 5 | 31.28 | 3 | <.001 | 0.987 | 0.021 | 0.083 |
| 6 | 108.76 | 3 | <.001 | 0.946 | 0.056 | 0.161 |

Models 1 (traditional Theory of Planned Behavior), 3 (Planned Behavior replacing behavioral control with self-efficacy), and 6 (Planned behavior replacing behavioral control with self-efficacy and adding impression management) did not fit the data well. Model 1's RMSEA was above the suggested cutoff (.08) suggesting Model 1's paths were misspecified. Model 3 and 6's CFI and RMSEA were below (.95) and above (.08) their respective cutoffs. Again, this suggests complex misspecification due to path coefficients. As these models are not plausible representations of the data, it is not proper to interpret path coefficients. However, an examination of the correlation matrix can prove useful. For Model 1, the low correlation of behavioral control to intention (.298) and engaging in activism (.190) are likely the cause of misspecification in this model. For Model 3, the moderate correlations between efficacy and intention (.395) and online activism (.322) may have split the impact of efficacy in this model. Finally, Model 6, had the same efficacy paths as model 3 and added a direct path from impression management to activism. Given the weak correlation between impression management and the other constructs in the study, this is likely the source of misspecification.

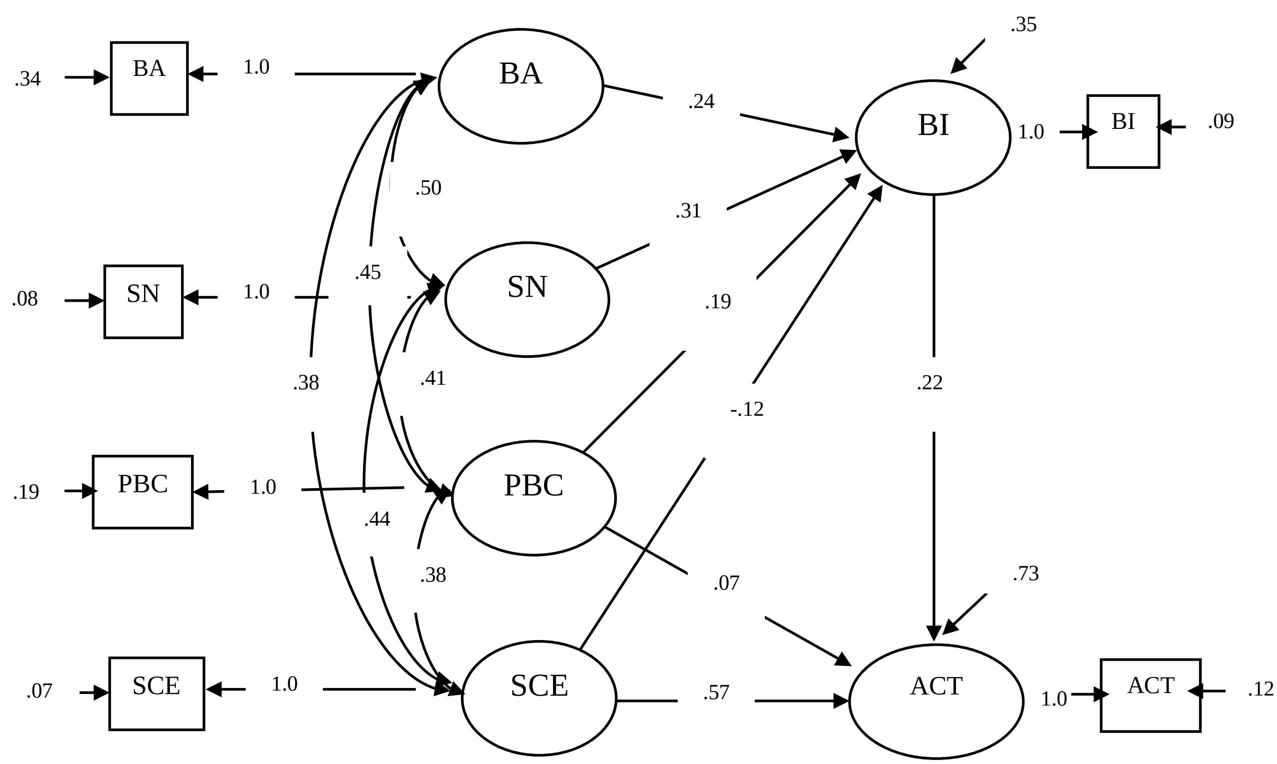
However, the three other a priori models yielded better model data fit. Model 4 is the same as Model 2 with the addition of a direct path between impression management and online activism. Model 4 fit the data relatively well ($\chi^2_{sb}$ (3) = 30.40, $p$<.001, SRMR = .024, RMSEA = .082, CFI = .986). In examining the structural equations to analyze path coefficients and the relative impact of each endogenous variable on the exogenous variables interesting results emerged. In predicting behavioral intention, attitudes ($\beta$ = .218, $p$ < .001), norms ($\beta$ = .294, $p$ < .001), and control ($\beta$ = .218, $p$ < .001) were all significant combining to explain 33.4% of the variance. In predicting activism, contradictory to predictions, behavioral intent ($\beta = .069$, $p < .001$), was statistically, but not practically significant while behavioral control ($\beta = .225$, $p < .001$), and impression management ($\beta = .549$, $p < .001$) emerged as practically significant explaining 73% of the variance.

Further examining the model using $\chi^2$ and covariance residuals, one immediate cause for concern is the relatively large value of the $\chi^2$. Additionally, the covariance residuals ranged from -3.91 to 2.56 with the residual between impression management and intention (-3.91) the largest. This indicates the model was misspecificed between impression management and intention given the set of constructs included in Model 4. Additionally, there were a total of 4 covariance residuals above $|1|$ and only a few approached zero. Because of the covariance residuals and the high $\chi^2$ Model 4 can be rejected in favor of stronger models for this data.

Model 5 is the most complex model, including all the constructs under investigation. Model 5 fit the data relatively well ($\chi^2_{sb}$ (3) = 31.28, $p$<.001, SRMR = .021, RMSEA = .083, CFI = .987). Attitudes ($\beta = .243$, $p < .001$), norms ($\beta = .309$, $p < .001$), and control ($\beta = .193$, $p < .001$) were all significant predictors of behavioral intention. Efficacy, on the other hand, was a negative, but not practically significant ($\beta = -.120$, $p < .001$) predictor of behavioral intention. The combination of attitudes, norms, control, and efficacy explained 36% of the variance in behavioral intention. Again, contradictory to predictions, behavioral intent ($\beta = .065$, $p < .001$), was statistically, but not practically significant while behavioral control ($\beta = .206$, $p < .001$), and efficacy ($\beta = .577$, $p < .001$) were significant predictors of online activism. Interestingly, in contrast to Model 4, impression management's impact on online activism becomes negative and practically insignificant when efficacy is added to the model ($\beta = -.113$, $p < .001$). The combination of behavioral intention, behavioral control, efficacy, and impression management explained 73% of the variance in online activism.

Again, the $\chi^2$ is relatively high, but all the covariance residuals are well below $|3|$ ranging from -.036 to .037 with many values approaching zero. Model 2 fit the data better than any of the other tested models ($\chi^2_{sb}$ (2) = 17.03, $p$=.001, SRMR = .013, RMSEA = .074, CFI = .99). The RMSEA value is slightly above the value (.06) proposed by Hu and Bentler (1999), but within the range (.05 - .08) used by Brown and Cudek (1993). RMSEA weights misfit per degree of freedom; thus, because Model 2 only has 2 degrees of freedom, the RMSEA value may be inflated. When viewed in conjunction with $\chi^2$, SRMR, and CFI the RMSEA is acceptable. All the covariance residuals were between -.006 to .039 indicating near perfect model data fit as indicated by the CFI and SRMR. The $\chi^2$ is nearly half the value of Model 5 indicating stronger fit. As these models, (2 and 5) are nested, we can calculate a $\chi^2$ difference test to determine if Model 5 fits the data significantly worse than Model 2. The result of a $\chi^2$ difference test ($\chi^2_{sb}$ (1) = 14.25, $p$<.001) is significant indicating that Model 2 fits the data significantly better than Model 5. Next, path coefficients for Model 2 will be discussed. Direct, indirect, and total effects, standard errors, z-tests, are shown in Table 5 while the path coefficients, disturbance terms, and variance explained are shown in Figure 3.

**Figure 3.** Model 2 with coefficients, disturbance terms, and error variances




The results indicate behavioral attitude (β = .238, $p$ <.001) and subjective norms (β = .307, $p$ <.001) were strong positive predictors of behavioral intention. Behavioral control (β = .192, $p$ <.001) and efficacy (β = -.115 $p$ <.001) while significant predictors of behavioral intention had smaller path coefficients, and efficacy had a negative path coefficient when combined with the other predictors in the model. In analyzing how the model predicts online activism an interesting result emerged. When combined with behavioral control and self-efficacy, the relative impact of behavioral intention in predicting online activism was diminished. Though still statistically significant, behavioral intention ($\beta = .072$, $p = .002$) was not practically significant predictor of online activism. However, behavioral control ($\beta = .215$, $p < .001$ and efficacy ($\beta = .566$, $p < .001$) were both strong predictors. This suggests that, when combined with self-efficacy and behavioral control, behavioral intention's predictive utility for online activism is diminished. The model accounted for significant variance in both behavioral intention (35%) and online activism (73%).

**Table 5**. Direct, Indirect, and Total Effects, Standard Error, and Z-Tests for Model 2

| | Intention | | | Activism | | |
|---|---|---|---|---|---|---|
| Variable | Effect | SE | z-test | Effect | SE | z-test |
| **Attitude** | | | | | | |
| Direct Effect | 0.238 | 0.05 | 5.29 | -- | -- | -- |
| Indirect Effect | -- | -- | -- | 0.017 | 0.01 | 2.54 |
| Total Effect | 0.238 | 0.05 | 5.29 | 0.017 | 0.01 | 2.54 |
| **Norms** | | | | | | |
| Direct Effect | 0.307 | 0.04 | 7.69 | -- | -- | -- |
| Indirect Effect | -- | -- | -- | 0.02 | 0.01 | 2.72 |
| Total Effect | 0.307 | 0.04 | 7.69 | 0.02 | 0.01 | 2.72 |
| **Control** | | | | | | |
| Direct Effect | 0.192 | 0.04 | 4.37 | 0.215 | 0.03 | 7.92 |
| Indirect Effect | -- | -- | -- | 0.014 | 0.01 | 2.75 |
| Total Effect | 0.192 | 0.04 | 4.37 | 0.229 | 0.03 | 8.97 |
| **Efficacy** | | | | | | |
| Direct Effect | -.115 | 0.03 | -3.55 | 0.566 | 0.02 | 24.2 |
| Indirect Effect | -- | -- | -- | -0.01 | 0.04 | -2.24 |
| Total Effect | -.115 | 0.03 | -3.55 | 0.556 | 0.02 | 24.11 |
| **Intention** | | | | | | |
| Direct Effect | -- | -- | -- | 0.724 | 0.024 | 3.06 |
| Indirect Effect | -- | -- | -- | -- | -- | -- |
| Total Effect | -- | -- | -- | 0.0724 | 0.02 | 3.06 |

## DISCUSSION

This research aimed to test six competing models of the Theory of Planned Behavior in predicting online activism among a sample of millennial students. It represents a starting point in helping nonprofit organizations understand why millennials engage in online activism and how organizations can use this knowledge to generate online support more effectively. Additionally, this research tests the theorizing that online activism (termed slacktivism by some) is primarily motivated by impression management motives.

First, models of TPB were tested to predict online social cause advocacy. While the traditional model of TPB did not fit the data well, the addition of self-efficacy, consistent with previous theoretical amendments to TPB, did fit the data well. In fact, the only viable model after analysis is TPB with self-efficacy added. Self-efficacy emerged as the most powerful direct effect on behavior. Second, evidence of a potential context effect for behavioral control emerged such that its predictive utility is lower when predicting online activism compared to a dietary or other health change. Third, impression management was tested in addition to the other predictors in TPB to assess its predictive utility in relation to other predictors. When impression management was included in TPB with self-efficacy, the impact of impression management on behavior was insignificant.

The results of this study suggest the psychological constructs tested, namely self-efficacy, subjective norms, and attitudes toward behavior, do predict a person's behavioral intention and actual behavior. This key finding should help nonprofit organizations in pursuit of millennial stakeholders develop an online strategy. Indeed, the frequency of social media activism found in this study among the millennial sample should provide an incentive for nonprofit organizations to value setting a social media strategy.

Organizations can use these themes to build social campaigns and develop messages to increase these beliefs. Recognizing that individuals are motivated by these three key constructs, organizations have a strategy roadmap. Once decisions about mediums (Facebook, Twitter, Instagram, TikTok, etc.) are made, organizations can begin to develop these campaigns knowing their strategies are based on research about what motivates their millennial stakeholders.

The combination of these findings and previous research that indicates online activists are also engaged in other, more traditional, forms of activism (Center for Social Impact Communication, 2011) represent a tremendous opportunity for nonprofit organizations and leaders as they use social media more strategically and effectively in pursuit of organizational missions.

This research sought to understand the psychological constructs that can help predict a person's intention to and actual engagement in online activism behavior using the Theory of Planned Behavior. Gaining a better understanding of how and why stakeholders make decisions to engage or not in social media activism can help organizations more strategically use social media in pursuit of their missions. For advocacy organizations, the question is not if, but how to use social media. This research aimed to provide an understanding of what can predict online social activism. The findings support TPB with self-efficacy added to the model as a viable way to predict online activism behavior.

Advocacy leaders can use the findings of this research to begin to test social media campaigns that aim to increase positive attitudes toward social activism, create social norms that support social activism, and increase self-efficacy toward generating social change via online activism. The combination of these findings and previous research outlining message strategy (Preston, 2010), a dialogic approach (Sisco & McCorkindale, 2013), and consistency can begin to help organizations formulate social media strategies that should produce increased engagement. Online activists are engaged online, and emerging research has indicated they are also active in offline activities such as donating, calling on representatives, and volunteering (Center for Social Impact Communication, 2011). These stakeholders represent a promising group of potential supporters organizational leaders should be strategically engaging, and this study is a step toward helping organizations develop appropriate strategies.

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