ABSTRACT

HAROLD, SERA. Rationale for and Relationship of the Thesis and Dissertation Requirement to Research at North Carolina State University. (Under the direction of Dr. Carla C. Johnson).

Environmental educators strive not just to put relevant and accurate information into the hands of citizens but to help ensure that information translates into actions. This dissertation explores the impacts of social networking sites such as Facebook on pro-environmental behaviors. Although research on social media use in education is in its early stages, existing empirical studies show mixed results about whether and in what contexts online educational interventions impact pro-environmental or green behaviors. This mixed methods study uses structural equation modeling, thematic and content analysis to estimate the complex relationships between social media engagement, social norms, self- and collective efficacy, age, gender and pro-environmental behavior. A survey of 1521 native plant-focused Facebook Group users and an analysis of posts within the Group were used to characterize the relationships between constructs. This research finds that engagement with social media predicts pro-environmental behaviors, mediated by self-efficacy and injunctive social norms. As more and more people around the globe obtain their environmental knowledge through social media, educators have an opportunity to influence individual and societal behaviors to address the imminent environmental crises humans will have to address in the coming years. This research identifies self-efficacy through skill and confidence development and injunctive norm perception as best practices for social media-based environmental education in a social media space.

Keywords: pro-environmental behavior; social media; social norms; efficacy; structural equation model; native plants

Native Plants-Focused Facebook Groups' Impacts on Users' Norm Perception, Efficacy, and Pro-Environmental Behaviors

by
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BIOGRAPHY

I had an unusual childhood, thanks to my family's wanderlust. I grew up traveling the world as my father trained teachers in North Carolina, Taiwan, and finally in St. Croix, USVI where I call home. I first met the Caribbean Sea in 1986, and the reef die-off over the following decades greatly impacted my environmental curiosity and anxiety. My childhood was full of sailing the Caribbean and snorkeling the dying reefs around St. Croix. In high school, I met my high school biology teacher, a sea turtle biologist, who mentored me and got me my first job researching sea turtles and protecting nests from poachers. She also ran the education program, taking school kids out to release leatherback sea turtle hatchlings and watch the females nest. I fell in love with the turtles of course, but also with providing people with nature experiences, with sharing my own awe.

After studying biology at Cornell, I went into the Peace Corps in Panama, working on an island that traditionally harvested sea turtles during mass nesting events, and now was switching to ecotourism. I helped train local egg collectors to be tourism guides and helped set up a hatchery for the eggs. This experience was amazing and solidified for me that my passion was where people and wildlife interacted. After the Peace Corps, I enrolled in a Master's degree at Duke's Nicholas School of the Environment, where I studied at Duke's marine lab with some amazing scholars and role models. I then went to work in Key West at the National Marine Sanctuary, where I did outreach and education, teaching college courses and leading snorkeling field trips.

My next adventure involved a decade working in fisheries advocacy, as I worked with a large team to (almost) end overfishing in the U.S. In 2012 I moved to a farm in West Virginia to found and manage a non-profit earth skills school called the North American Bushcraft School. I

homesteaded at the farm, raising crops, turkeys, goats, and chickens, and taught herbalism, fermentation, natural dyes, Leave No Trace, and wilderness medicine classes.

In 2020, my father, at 80, needed help, and I returned to North Carolina to care for him and finally complete my education with a doctorate. My early experiences in environmental education and conservation research inform my interest in finding tools for successful societal change. Studying science education is a culmination of my intersectional early career, and I am fortunate to have had the opportunity.

In the years ahead I will continue to educate and advocate for a sustainable relationship with our planet both in and out of classrooms. Socio-environmental issues have become increasingly urgent in the 30 years I have worked in the field, and we will need an armada of educated and motivated young people to continue the effort. In the latter part of my career, my goal is to close the loop, mentor, and teach.

ACKNOWLEDGEMENTS

I want to acknowledge all the incredible teachers I have been fortunate enough to have. I can only aspire to be the kind of educator I have had in my life. First, I thank my first teachers, my wonderful parents Gary Harold and Jolynn Uban, and my siblings Jesse and Aaron, who encouraged my passions and had to listen to me talk about turtles and fish for so many years. I was fortunate to have Amy Mackay-Harvey as my high school biology teacher and mentor and the many people at the Refuge and Park Service who taught me about field research, bucket marks, and constellations.

This work would not have been possible without my committee, especially my advisor and committee chair Dr. Carla C. Johnson, who has been patient and supportive during the many drafts and iterations of this research.

I want to acknowledge Ana Topliceanu for helping me code the seemingly endless data for this study. I also sincerely thank the Docksiders of Chapel Hill, whose Wednesday night music jam sessions helped me maintain my mental health during my doctoral studies. Finally, I want to acknowledge my uncle Issy AhKuoi, who did my dishes when I had deadlines and reminded me to leave the study occasionally.

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CHAPTER 1:

INTRODUCTION

Research Problem

Environmental crises in climate, pollution, and biodiversity are complex and pressing global issues that require an informed and engaged citizenry to address. A 2020 Pew Research Center poll found that Americans ranked the environment at the top of their national priorities, outpacing economic and security concerns (Atske, 2020). Unfortunately, environmental education has lagged in reaching its goal of creating an informed and active citizenry. Most Americans (89%) cannot pass a basic environmental literacy test (Coyle, 2005), and environmental education is not a priority in K-12 schooling (Bentley, 2010). Americans' environmental knowledge comes predominantly from media (95%), while only 5% is attributed to formal schooling (Coyle, 2005). Social networking sites (e.g., Facebook, Instagram, Reddit) represent an increasingly large share of that media ecosystem. The power of social media to educate and inform about rapidly changing science and circumstances is an under-studied force in the lifelong learning environment (Ahmed et al., 2019). A recent poll by the Pew Research Center (2021) found that almost half (45%) of adults 18-26 years of age interact with climate change information on social media on at least a monthly basis. Americans' environmental knowledge levels and the changing nature of media use present serious challenges to our ability to address the persistent environmental problems in our future.

We are currently in the midst of the Earth's sixth mass extinction. One in every four insect species has gone extinct in the past 200 years, primarily due to habitat loss (Fonseca, 2009). Bird, butterfly, and insect populations depend on a high percentage of native plants (70%) to feed and reproduce; however, our urban and suburban landscapes are around 70% exotic species instead (Narango et al., 2018). Promoting native planting and removing invasive exotic species is the purpose of the North Carolina Native Plant Forum (NCNPF), The California

Native Plant Society (CNPS), and many other interest groups formed on Facebook. These Groups provide users with a steady flow of information and advocacy, and the NCNPF and CNPS reach 90,000+ Facebook feeds daily.

While engagement with social networking sites (SNS) such as Facebook Groups has given individuals a forum to engage with critical discourse regarding native planting behaviors, it has been challenging to determine how functions of SNSs can inform and support pro-environmental behaviors (Li et al., 2019). In fact, studies have produced mixed results revealing that these behaviors may be context-dependent (Bolderdijk et al., 2013; Boulianne & Ohme, 2022; Dono et al., 2010). What works in one context for a particular pro-environmental behavior (PEB), like recycling, does not work for something else, such as energy savings. A Facebook Group like the NCNPF has its own context and culture. Each Facebook Group is administered and moderated differently, with some limiting posts on specific subjects (e.g., insects). As a result, some Groups become more focused on, for instance, on field identification, while others focus on photographs of native species. These SNS learning communities are being studied for their various capabilities, but few studies address them as places to encourage PEBs in the area of biodiversity (Allison et al., 2023; Ma et al., 2021; Robelia et al., 2011). One of these few studies is a qualitative analysis of a South African recreational fishing Group on Facebook (Allison et al., 2023). Over time, this Group helped reinforce social norms around responsible fishing techniques, though the authors could not attribute this change to the Group itself (Allison et al., 2023). This dissertation will explore the educational value of native plant forums and how they influence the pro-environmental behaviors of their users.

Environmental Education

Environmental education, in its most fundamental form, has been practiced by people all over the globe for millennia (Kowalski, 2019). Some of the earliest human stories are about the sacredness of wilderness and caring for the environment (Weyler, 2018). In the Mesopotamian story of Gilgamesh (written around 2500 BCE), dire warnings are issued to anyone who felled trees in the disappearing forest. Warnings of more modern global environmental crises like climate change came at the dawn of the 20th Century, in 1896, from a Swedish scientist (Lipsky, 2023). However, it would be another 80 years before the United Nations took up the issue of environmental crises and education.

The United Nations was formed in 1945, and 30 years later, it formed the Belgrade Working Conference on Environmental Education (1975) and the Tbilisi Intergovernmental Conference on Environmental Education (1977). The 1977 conference produced the Tbilisi Declaration, which states that

> [e]nvironmental education is a process aimed at developing a world population that is aware of and concerned about the total environment and its associated problems and has the attitudes, motivations, knowledge, commitment, and skills to work individually and collectively towards solutions of current problems and the prevention of new ones (UNESCO, 1977, p. 3).

For nearly 50 years, this report has served as the foundation for environmental education worldwide, setting out broad goals and objectives. Hence, environmental education transmits facts, understandings, and motivations to act pro-environmentally. The 1970s also saw the birth of the United States' (U.S.) environmental movement in response to increasing environmental concerns.

Pro-Environmental Behaviors (PEBs)

One goal of environmental education is personal and societal behavior change (Stapp, 1969). Increasing someone's environmental knowledge is of limited use to the broader society if that education fails to produce PEBs. These can vary from recycling, using public transportation, and making green purchases to energy use reductions, landscaping choices, and reducing litter and food waste. These examples require different knowledge and behavioral supports (Robelia et al., 2011). Researchers have explored several models of PEBs, each focusing on slightly different aspects of PEB development. The popularly used models of PEB, like the theory of planned behavior (Ajzen, 1991) and norm activation theory (Schwartz, 1977), have limitations (Grilli & Curtis, 2021). These models discount the role of education in PEBs because they apply outside of educational contexts and because the link between education and behavior is notoriously difficult to trace due to the number of influences on individual human behaviors (Grilli & Curtis, 2021). Many researchers have concluded that while education can impact pro-environmental intention (PEI), a suite of factors having little to do with knowledge (i.e., fear of environmental impacts, guilt, social norms) influence behavior more directly (R. Han & Cheng, 2020; D. Li et al., 2019; Mónus, 2021).

Another limitation of commonly used models of PEBs is that the measured impact of these interventions can be small or nonexistent (Karimi et al., 2021; Williams et al., 2021; Zhang et al., 2022). The scale of the environmental problems at stake means that our interventions must significantly affect human behavior. Most of these interventions to increase PEBs involve some form of education followed by measurement of the specific PEBs (i.e., recycling, energy use). The influence of education on pro-environmental intention to act (PEI) is evident (Grilli & Curtis, 2021; D. Li et al., 2019), but the transition from intention to behavior, referred to as the "education-behavior gap" (Kollmuss & Agyeman, 2002), involves an additional set of

influences. These influences are described by the Theory of Planned Behavior (TPB; Ajzen, 1991) in the context of how social networking sites encourage PEBs.

Social Media & Environmental Education

Social media is a broad term that encompasses any online communication and can include online news sites, company websites, and social networking sites (SNSs) like Instagram, Facebook and Twitter (TheGovLab, 2021). Social networking sites are a subcategory of social media in which two-way communication and user content are the central mode of communication (TheGovLab, 2021). In 2003, the social media pioneer MySpace launched, ushering in sweeping changes to human social networks, communication, news consumption, and more (Ahmed et al., 2019). Seventy-two percent of Americans in 2022 said they used social media, and 69% singled out Facebook, the most widely used social networking site worldwide. A recent study found that social media accounts for 39% of the average American's media consumption, though it is higher (62%) for young adults than for older (19%). Moreover, 7 of 10 Facebook users visit their feed daily (Spangler, 2022). Social media is a fast-growing part of the media consumed by Americans. Not only are TikTok videos and Facebook memes ubiquitous in the media landscape, but the combination of informational and social interaction offered by social media offers more promising pathways for pro-environmental behavior change than traditional media campaigns (Allison et al., 2023; Borg, 2022; Boulianne & Ohme, 2022; Chung et al., 2020; Gonzalez et al., 2023; R. Han & Xu, 2020; Kumar & Pandey, 2023; Li & Noor, 2022; Ma et al., 2021; Robelia et al., 2011)

Study Context

Though many social networking sites exist, this dissertation study utilized Facebook Groups, which boasts 1.8 billion monthly users (TheGovLab, 2021). Specifically, the North

Carolina Native Plant Forum (NCNPF), Native Plants of the Northeast (NPNE), and the California Native Plant Society (CNPS), three Facebook Groups focused on environmental education, each with more than 80,000 members in 2024, were the focus of this study. These Groups are roughly analogous to Twitter hashtags or subReddits in that they focus on a single subject, but unlike hashtags or subReddits, the NCNPF, NPNE, and CNPS are public forums, and members must apply for membership by meeting criteria such as living in the state or region of interest and by answering questions about their learning goals. Moderators of the forums can revoke membership and block user comments. One benefit of these moderated Groups is that misinformation is quickly removed and corrected, and the norms of the Groups are enforced. For example, in the NCNPF, no praise of exotic species is allowed, and moderators will remove any post that admires Chinese privet or crepe myrtles.

Purpose Statement & Research Questions

Existing empirical studies of SNSs such as Facebook as tools for encouraging PEBs are limited in number and do not yet describe the factors of PEBs in a wide array of contexts (Li et al., 2019). This is especially important since the factors leading to PEBs, such as social norms and self-efficacy, are context-dependent (Grilli & Curtis, 2021). Several studies have provided hypotheses about social media's influence on PEBs (Borg, 2022; R. Han & Cheng, 2020a; Ma et al., 2021). Borg's (2022) study of 1,001 Australian adults' plastic use and media exposure found that social media activated descriptive social norms (what others are doing) while televised and print media activated injunctive norms (what should be done). Han and Cheng (2020) found a similar pattern among 550 Chinese adults' general PEBs. We do not know how these relationships hold up in the United States' media ecosystem or under different conditions, but studies have shown that the particular media ecosystems of different countries can play a role in

how they influence PEBs (Zafar et al., 2021; Zhang & Zhong, 2020). Studies on social media and efficacy show that political engagement is encouraged by social media through collective efficacy (Velasquez & LaRose, 2015), but we do not yet know how collective efficacy from social media impacts PEBs. This dissertation explored how social media sites such as the North Carolina Native Plant Forum on Facebook encourage environmental learning and how they influence the PEBs of its users through factors such as social norms and efficacy. The research questions which guided this study were:

1. What are individuals' native planting practices/PEBs, and how much can users' PEBs be attributed to participation in a Facebook Group?
2. How do key factors (social norms, social media engagement, self-efficacy, collective efficacy, financial barriers, regulations, age, and/or gender) interact to predict individuals' PEB?
3. What types of learning outcomes result from participation in the Facebook Group, and does the duration of membership impact this learning?
4. What are the differences in rules, moderation, virality, nature of the online discourse, and associated impact on promoting PEBs in three regional Facebook forums?

The findings of this study will inform environmental education strategies for encouraging PEBs, utilizing SNSs such as Facebook. This dissertation and the existing body of research indicate that effective educational outreach through social media should be highly tailored to the audience and the targeted behavior. The results of this study, which describe the forum's users, are helpful to practitioners targeting environmental information to particular audiences.

Overview of Methodological Approaches

This study used a mixed methods design, represented in Figure 4, to answer the research questions posed in this paper. Mixed methods are defined as those that include both quantitative and qualitative analysis (Creswell & Plano Clark, 2011). The particular study design used in this research is also fixed and embedded. A fixed study is determined to be mixed methods at the beginning of the study, whereas an emergent mixed methods study happens in response to needs or problems during the study (Creswell & Plano Clark, 2011). Fixed mixed methods are often chosen in order to triangulate and enrich data. An embedded study describes the overall design and prioritization of quantitative and qualitative data (Merriam & Tisdell, 2016). Embedded research is primarily either quantitative or qualitative, with the other data form added for a specific reason. Finally, mixed methods studies can be concurrent or sequential in terms of data collection. In a sequential study design, one form of data is collected first, thereby informing the collection of the other data strand (Creswell & Plano Clark, 2011).

A fixed embedded and concurrent mixed method approach was chosen for this study for a variety of reasons. Mertens (2020) argues that mixed methods are beneficial for problems in complex social or educational contexts, which aptly describes social media platforms. The author chose a mixed methods design after previous qualitative research projects on this subject highlighted the need for quantitative data to enable comparisons with similar research abroad. The embedded design with quantitative data at its center was chosen because the intended qualitative data (content analysis and two open-ended questions on a survey) was not robust enough for its own qualitative study. Instead, it was intended to triangulate the quantitative data. Triangulation is defined by Merriam (1998) as the use of multiple methods, investigators, or sources of data to confirm emerging findings. In this study, triangulation was deemed necessary because any one of the data sources used is insufficient on its own for answering the research

questions, which is the purpose of the embedded mixed method. The qualitative data provides a personal and specific view of the Group and its impacts, while the quantitative data provides a larger overall view of the phenomenon.

Survey

This dissertation study included developing and administering a survey to assess key factors in native planting, discovering how different demographic groups engage with these social media sites, and determining how the forum impacts users. The survey design and validation process followed guidelines from DeVellis and Thorpe (2022), including various validity measures, piloting, and confirmatory factor analysis. The survey contained 31 total questions, including 28 quantitative questions related to demographics, social media engagement, social norms, and efficacy, and two open-ended questions about learning outcomes and enacted pro-environmental behaviors. Quantitative survey data were analyzed using a structural equation model (SEM) to examine the relationships between the various concepts and PEB. SEM involves developing a theoretical model of the concepts' relationships, identifying the model for solvability, and respecification of the model. Qualitative data from the survey's open-ended questions underwent thematic analysis to identify trends in the self-reports of learning outcomes and pro-environmental behaviors. This thematic analysis involved multiple rounds of inductive and a priori coding to characterize these data with greater reliability.

Content Analysis

The three Facebook Groups' discussion pages were sampled for content analysis to fully answer the research questions and provide a greater understanding of the way these groups encourage PEBs. Fifty consecutive posts, along with the first five comments and all virality metrics (shares,

comments, and likes), were sampled from each page and underwent a priori thematic coding and analysis for trends and patterns.

Significance

A robust body of research regarding strategies that encourage PEBs exists (Grilli & Curtis, 2021), and there is a rapidly growing body of knowledge on the use of social media for environmental education (Chung et al., 2020; Gonzalez et al., 2023; R. Han & Xu, 2020; Meng et al., 2023). However, few studies exist at the intersection of the two concepts or in the U.S. (United States) context (Grilli & Curtis, 2021). Those that do exist show mixed results in encouraging PEBs, and many studies show no or minimal impact of education on PEBs (Bolderdijk et al., 2013; Borg, 2022; Ma et al., 2021; Young et al., 2018). These researchers disagree about whether and to what extent environmental education interventions increase PEBs. The various tested interventions and PEBs have varied results (Bolderdijk et al., 2013; Borg, 2022; Ma et al., 2021). More granularity in the context, specific PEBs, and specific social media platforms are needed to understand why PEBs change sometimes and not others. Studies from China and Australia suggest that social media activates descriptive norms and drives more PEBs, whereas traditional media in China activates injunctive norms and fails to encourage PEBs (Borg, 2022; R. Han & Xu, 2020; W. Han et al., 2023; Ma et al., 2021). This study will quantitatively examine these relationships in a U.S. context for the first time. In addition, collective efficacy has not been measured in the U.S. as a precursor of PEB or in comparison with other concepts such as self-efficacy and social norms.

Environmental educators and activists struggle with getting information to people where and when they need it to make sustainable decisions. Social media has distinct advantages for this kind of just-in-time education, including being available 24/7 on smartphones, being much

less expensive than traditional media campaigns, and its ability to reinforce social norms through user-generated content and virality metrics. Social media-based environmental campaigns, however, have a mixed track record. This dissertation will contribute to the literature on social media's impact on PEBs. The mediation of this impact by efficacy, gender, and social norms in the U.S. context has not been studied.

Summary

The ever-increasing use of social media shows promise as a place for environmental learning because of its unique characteristics. Sites such as Facebook are available 24/7 at practically any location, contain vast amounts of information (of variable quality), and provide social support important to sustained behavior change over time. This study used survey data and Facebook Group content to explore the power of a Facebook Group to encourage its users' pro-environmental behavior around the issue of biodiversity loss in our landscapes.

CHAPTER 2:

LITERATURE REVIEW

Environmental education primarily occurs in informal settings, and especially in the media. That media landscape is changing, and Americans use social media for a substantial and increasing part of their media diets. Researchers worldwide have begun to view social media as an opportunity due to the functionalities of platforms such as Facebook, which incorporate social pressures and interactive learning into knowledge-based media. Theories such as the TPB hypothesize that these functions should positively impact behavioral outcomes. Studies worldwide show the complexity of behavioral change within different cultural contexts, different media ecosystems, different PEBs and different SNSs. This dissertation explored the cases of three Facebook Groups for native landscaping and how these factors impacted PEB.

In order to understand social media as a learning environment with the ability to increase the PEBs of its users, this chapter will first provide background and relevant research on general environmental literacy and knowledge acquisition, learning in social media spaces, and multi-media learning's power to increase learning outcomes. Second, this chapter discusses Ajzen's Theory of Planned Behavior (TPB; 1991), and the various concepts that predict PEBs, including pro-environmental intention, social norms, self- and collective efficacy, demographics, virality, and social media engagement. This is followed by a discussion of the Technologies for Pro-Environmental Action Model (TPAM, Ballew et al.,2015) and social media's role in encouraging PEBs. Finally, this chapter discusses research on the ecological importance of native plants in landscaping and explores previous studies of native landscaping as a PEB. These previous studies point to gaps in our knowledge about how norms, efficacy, social media, and demographics interact in US populations to encourage PEBs, what PEBs and learning outcomes result from these online learning communities, and how to use social media to encourage PEBs more successfully.

Environmental Literacy

The United Nations defines environmental literacy as "a basic functional education for all people, which provides them with the elementary knowledge, skills and motives to cope with environmental needs and contribute to sustainable development" (UNESCO/UNEP, 1986, p.3). It is further described as consisting of four major areas: knowledge, skills, affect, and behavior, where affect consists of environmental sensitivity, attitudes, and values (Roth, 1992). PEBs, therefore, are one part of environmental literacy that is often accompanied by environmental knowledge, skills, and affect. For individual behaviors to positively impact biodiversity in our landscapes, people must possess some level of environmental literacy (Anderson et al., 2021). There are no recent national measures of adult environmental literacy in the U.S. (a benchmark assessment was completed in 2005), but several data sources, such as polls on climate topics, give us important clues.

A 2010 Gallup poll found that Americans are participating in more PEBs than ever, with almost 60% recycling and 30% purchasing green products (Gallup, 2010). More recent polling suggests that environmental concerns have returned to the top of many Americans' priority list, with 71% of millennial adults (born 1981 -1996) listing environmental issues as their top concern (Pew Research Center, 2021).

Not all research on environmental literacy, however, paints a green picture. Environmental knowledge and concern are highly polarized issues in the United States, with significant differences in knowledge and concern between the two major political parties (Coyle, 2005) and among religious groups (Drummond & Fischhoff, 2017). Overall, Americans' general environmental literacy is limited. A benchmark survey from 2005 measured adult environmental literacy in the U.S. It found that less than 30% of U.S. adults know enough about climate change

to make informed consumer and voting decisions (Coyle, 2005). However, studies have also found that overall education and scientific literacy do not significantly contribute to concern for environmental crises, and that demographic factors, such as political party affiliation and religious alignment, are more salient (Fischer et al., 2022).

While overall education and environmental literacy may not impact environmental concern (a value orientation towards specific and general PEBs; Fransson & Gärling, 1999) linearly, informal, and lifelong environmental education has proven critical for collective action by raising issue awareness (Abrahamse, 2019). The science and socio-political contexts of environmental crises change constantly, and specific, place-based environmental education is crucial for encouraging pro-environmental behaviors (Johnson et al., 2020). While environmental concern seems unaffected by knowledge, other important factors in PEB like efficacy and awareness are influenced by education, and this dissertation will focus on these salient factors.

Learning in Social Media Spaces

The use of social media in learning has been examined in both formal and informal contexts. Given the growth in social media use, this is critical to examine, especially for lifelong and environmental learning. Social media in informal contexts caters to interest-driven and lifelong learning (Greenhow & Lewin, 2016). The peer-to-peer nature of social media changes the roles of learner and teacher into a more collective and democratic endeavor (Leal Filho et al., 2018). Social media users across cultures report increased confidence in peer-to-peer sharing of information relative to TV and print media (Han & Cheng, 2020). Increased participation, interaction, engagement, low cost, and information sharing are benefits of social media as a learning environment (Santaoja, 2022).

Many learning theories include the concept of social learning (Adams, 2006; Amineh & Asl, 2015; Bandura, 2000). Early learning theorists such as Vygotsky and Dewey asserted that learning is, by nature, a social process (Reed et al., 2010), and various social theories of learning define social learning as participation in the practices of a community (Gruzd et al., 2016). The current research aligns with this conceptualization of social learning as "a process of social change in which people learn from each other in ways that can benefit wider social-ecological systems," as suggested by Reed and colleagues (2010). One example of this comes from researchers in Germany. A random digit dial survey of 1,214 German households showed that social media use was highly correlated with vegetarianism due to images of animal cruelty, vegetarian influencers, and perceived social norms (Kley et al., 2023).

Social media forums provide opportunities for rapid knowledge flow between people separated by time or distance, but with similar interests (Ahmed et al., 2019). This same systematic review of the literature identified three main individual activities within social media forums: knowledge seeking, knowledge contributing, and social interactivity. A study of 511 adult learners found that social media use enhances active learning, collaborative learning, and creativity (Khurshid et al., 2023).

Multimedia Learning.

Although research on social media-based learning is relatively recent, scholars have decades of accumulated knowledge about learning in multimedia spaces. This research shows that people can learn more from words and pictures than from words alone because they process audio and visual information through separate processes that create less cognitive load for the learner (Mayer, 2014). Multi-Media Cognitive Theory involves searching, perceiving info, interacting with it, followed by integration/critical reflection. When people's browser history and

eye movements are combined with reflections on climate change, researchers found a greater understanding of the content (Upadhyaya et al., 2023). Learners also construct knowledge from these words and pictures more easily when they are personalized and informal in tone (Mayer, 2014). This theory also states that educational technology is only useful when it is learner-centered instead of technology-centered. Learning that is designed with the human mind at its center leads to more meaningful knowledge (Mayer, 2014). A study of 64 teams found that social media use increased team bonding, efficacy, and knowledge sharing (Chen et al., 2023). Social media's social, multi-media experience should be conducive to environmental learning. This broad term "learning" includes measures beyond the accumulation of facts.

Learning Outcomes

Several studies have examined the ability of social media environments to enhance learning outcomes. These learning outcomes, as defined by the United Nations, include knowledge, skills, attitudes, and behaviors. Informal learning environments like social media often have learning outcomes other than knowledge gains (Phillips et al., 2014), which are not strongly correlated with increases in PEBs (Grilli & Curtis, 2021). Other kinds of learning outcomes include increases in awareness, efficacy, and behaviors (Phillips et al., 2014). Knowledge gains, which are the primary metrics in formal schooling, measure factual knowledge as with a multiple-choice test. Raising awareness, in the case of native plants, could be understanding the plight of native pollinators like the Monarch butterfly, or even developing an awareness of the prevalence of exotic plants in our landscapes. Increasing efficacy is another commonly measured learning outcome. Efficacy (one's confidence in their ability to complete a task) is generally closely correlated to increasing PEBs (Grilli & Curtis, 2021) and can include the mastery of specific skills that are needed to achieve the PEB. Learning to identify the

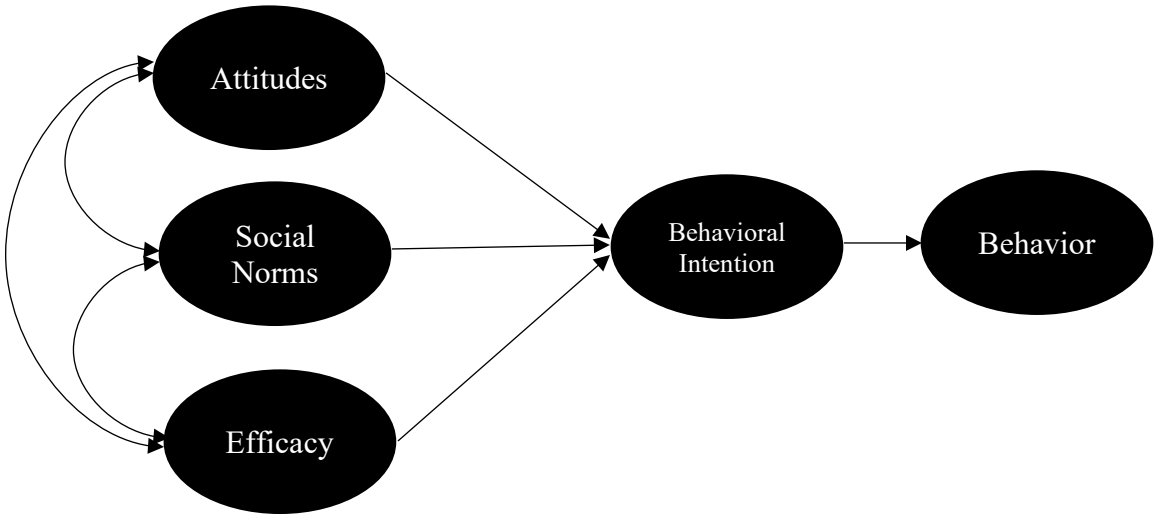
differences between a native and exotic holly bush, for example. These rehearsed skills give users confidence in their ability to complete PEBs like removing exotics and planting natives. Finally, PEBs themselves can be measured as outcomes of learning. The TPB hypothesizes that these gains in knowledge, efficacy, and attitudes, in turn lead to increases in PEBs (Ajzen, 1991).

Theory of Planned Behavior

This study is informed by the Theory of Planned Behavior, which argues that perceived behavioral control (efficacy), together with behavioral intention, can predict behavioral achievement (Ajzen, 1991). In the years since Ajzen's seminal paper on TPB (1991), the factors have expanded to include things such as social norms. This dissertation study focused on the behavioral controls and social norms interacting with social media to predict pro-environmental behaviors (PEBs). Figure 1 shows a TPB scheme showing the antecedents of behavior. According to TPB, an individual's attitudes, their perceptions of social norms, and their efficacy (belief in their ability to accomplish a goal) interact with each other to cause the intent to behave in a certain way. According to this theory, the behavioral intention then leads to the target behavior. Evidence from studies of PEBs show that these same antecedents are responsible for the conversion of intention to behavior (Abrahamse, 2019; Grilli & Curtis, 2021). For the purposes of this dissertation research, behavior is measured directly, and behavioral intention is eliminated from the model.

Figure 1

The Theory of Planned Behavior



Note. Adapted from Ajzen, 1991.

Pro-Environmental Behavior (PEBs) and Pro-Environmental Intention (PEI)

Pro-environmental behavior (PEB) refers to conscious actions taken to mitigate the negative impact of human activities on the environment or to improve its quality (Sawitri et al., 2015). Pro-environmental intention (PEI) is the desire or aim to engage in PEBs. Studies show that education is particularly effective at promoting PEI, but converting PEI to PEBs sometimes requires more than education (Wesley Schultz & Zelezny, 1999).

Many theories have been used to explain PEBs, and although convincing studies exist, overall results have been mixed. Some theories (including the Theory of Planned Behavior and Norm Activation Theory) discount the role of education or media use in the PEB process while emphasizing other precursors (Ajzen, 1991; Schwartz, 1977).

Some studied SNS interventions did not result in greater pro-environmental behavior (Geiger et al., 2019; Liobikienė & Poškus, 2019). In a survey of 1,058 SNS users in China, SNS

use was not correlated with PEBs, though it was correlated with pro-environmental intent (Liu & Li, 2021). Models showing the factors and influences on PEBs vary, but all include both internal and external influences. Some influences previously studied include demographics , social norms, barriers to behavior, education/knowledge, and self-efficacy (Grilli & Curtis, 2021). Researchers found that among British, U.S., Canadian, and French adults, age positively predicts participation in environmental marches and demonstrations (Boulianne & Ohme, 2022). Researchers Han and Cheng (2020) found that in China social norms were more important among social media users than traditional media users. In their review of relevant literature, Grilli and Curtis (2021) found that cost and convenience are two of the most important barriers to PEB. A Lithuanian study found that environmental education did influence PEB through the individual's worldview (Liobikienė & Poškus, 2019). A Chinese study found that self-efficacy was negatively correlated with how much media exposure a person experienced (Wei et al., 2024). These seemingly conflicting findings leave an evidence gap in the literature which this dissertation seeks to fill. Among these studies of social media's effects on PEB, many different models of PEB are used other than the Theory of Planned Behavior, and these diverse theoretical frameworks can influence the findings.

Models of PEBs

Differing predictive models of PEB are reflected in the literature, and each has benefits depending on the exact behavior and context under scrutiny. One study from China used a "mediation and moderation model," which included SNS usage, self-efficacy, and threat assessment (fear of personal impacts). Researchers found that all three were positively correlated with PEBs (Shah et al., 2021). Researchers Liu and Li (2021) found that media exposure to environmental messages, perceived personal responsibility, and environmental concern were

correlated with PEBs, but not self-efficacy. Another study from China adds "satisfaction with governmental environmental protection" as a significant variable and further finds that SNS use has variable results and that threat perception had small impacts on PEBs. There are dozens of factors explored in the extant literature that lead to PEBs, and each of the following models excels in certain circumstances.

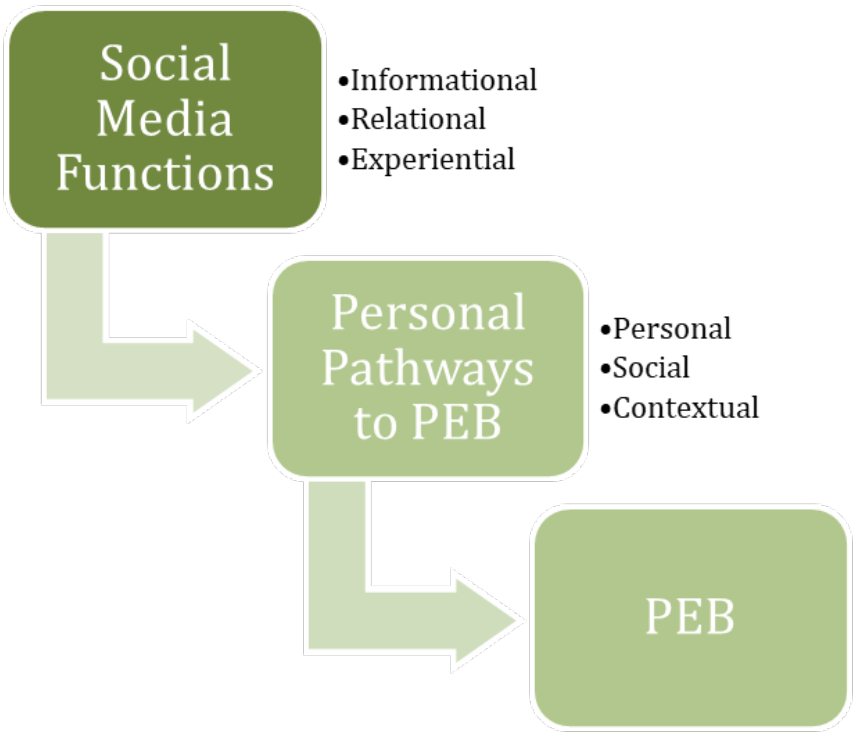
The Theory of Planned Behavior is a common model for predicting PEBs. It includes extensive cognitive factors such as efficacy (one's belief in their ability to achieve a goal) and normative and behavioral beliefs (beliefs about what is right, wrong and expected), but it does not deal directly with converting PEI to PEBs and generally leaves out education, self-efficacy, and feedback (Yuriev et al., 2020). The theory of planned behavior has been criticized for prioritizing attitudes over knowledge and habits (Stern, 2000). While TPB does not directly address the concepts of media engagement or collective efficacy, other theories do, and those theories were drawn upon for the creation of the model in this research.

The social cognitive theory of mass communication (Bandura, 2001), for example, posits that mass media creates collective efficacy, so that the more a group judges themselves to be successful in changing behavior, the higher their collective aspirations and investments in particular behaviors. Although Bandura wrote this theory before the emergence of social networking sites, the ideas around mass communication can apply to social media.

A review of literature conducted by Ballew and colleagues (2015) on the use of social media to encourage PEBs informed the conceptual Technologies for Pro-environmental Action Model. This model argues that social media is a successful intervention when its functionality aligns with the precursors of PEBs (Ballew et al., 2015). Figure 2 shows the basic structure of the TPAM model.

Figure 2

The TPAM Model of PEBs



Note. Adapted from Ballew et al., 2015.

This review (Ballew et al., 2015) categorizes different SNSs in terms of their informational, relational, and experiential functions, and rates Facebook as the most well-rounded of the popular U.S. SNSs. Informational functions of SNSs put user-generated or reprinted content at the fingertips of users, making information accessible, searchable, and curated (when the SNS is well-moderated). Relational functions of SNSs focus on social uses, community building, comments, dialogue, likes, norms, social emotional feedback, and inspiration. Experiential functions include novel online experiences, such as forums, interactive games, web tools, and training.

Precursors of PEBs

Studying complex human behaviors involves intersecting interests, contexts, and social/emotional factors. Studies of PEBs find a wide range of these factors relevant to the development of PEBs, including demographics, social norms, media engagement, self-efficacy, and various behavioral barriers such as cost and availability of native species (Grilli & Curtis, 2021). If we define environmental literacy as the combination of knowledge, skills, affect, and behavior (UNESCO/UNEP, 1986), these factors of PEBs align well with the ingredients for environmental literacy (Coyle, 2005).

Norms. Some of the strongest evidence for how to encourage PEBs comes from research on personal and social norms. Personal norms are described by Schwartz (1977) as social norms that have become integrated into an individual's cognitive structure. Personal norms are consistent and strong predictors of PEBs (Han et al., 2023; Quan et al., 2023). The same study from Han and colleagues found that social norms (external standards of behavior) are more effective when they have fully integrated and become personal norms and that social media mediates this process. Personal norms are significantly correlated with the sharing of climate info on Instagram, with participation in an organized environmental movement, and with green purchasing behavior (Jaini et al., 2020; Rajwade, 2024; Zhamaliveva, S. et al., 2023). Researchers have found, however, that not all social norms are the same (Hynes & Wilson, 2016). One study found that traditional media activate injunctive norms (you should not do this), which do not correlate to PEBs, while social media tends to activate descriptive norms (knowledge of what others are doing), which do correlate strongly with PEBs (Han & Cheng, 2020). In another study, Han and colleagues (2018) argued that user-generated content particularly strongly impacts descriptive social norms. A study of blog posts and comments questioning climate change science, revealed that readers' beliefs are influenced by the perceived

social consensus in the comments section (Lewandowsky et al., 2019). On Facebook these norms or consensus are indicated by like and share metrics. Eye tracking experiments confirm that social media users pay special attention to these normative metrics (Yang et al., 2024). Norms are often expressed in social media by metrics of virality.

Virality. A Korean experiment by Park and Jung (2023) explored the impacts of social media virality on PEI. They define virality as the number of likes, shares, and comments on a post, and they assert that these virality metrics communicate other people's attitudes towards a particular post (Park & Jung, 2023). These metrics carry social norm information by showing the social endorsements of others for particular content (Park & Jung, 2023). In these ways, virality metrics are argued to carry significance for social media's impact on PEB through social norms. Eye-tracking experiments confirm that social media users pay special attention to these normative metrics and use them to assess the reliability of the information (Yang et al., 2024).

Knowledge. Some researchers have found a negative correlation between environmental knowledge and PEBs (Han & Cheng, 2020; Xu & Han, 2019), while others have found a positive correlation (Han & Xu, 2020; Ummar et al., 2023). One qualitative focus group study of 29 people found that environmental knowledge is correlated with zero-waste behaviors on a Malay college campus (Baba-Nalikant et al., 2023). Another Malaysian study found that street food vendors who used social media had more knowledge about plastic in the environment and were likelier to engage in a plastic reduction program (Abdullah et al., 2022). Researchers in 2011 found that a climate change Facebook page's users had more knowledge and self-reported PEBs over time (Robelia et al., 2011). In the same study, a survey of 111 social media users found that only 33% of Americans knew how most energy in the U.S. is generated, but 89% of a Facebook Group's users knew the answer (Robelia et al., 2011).

Demographics. Another PEB antecedent with mixed empirical evidence is demographics. A relevant study of green purchasing behavior found that demographic characteristics correlated with PEBs more strongly than subjective norms or environmental awareness (Noubar et al., 2023).

Age. Shah and colleagues (2021) found a strong tendency for younger Iranians to participate in more PEBs, but this is an outlier. Most studies that consider age as a factor in PEBs indicated a strong tendency for older people to engage in more PEBs (Carducci et al., 2017; Dekoninck & Schmuck, 2022; Xu & Han, 2019; Zhamaliveva, S. et al., 2023; N. Zhang & Li, 2023). Younger people more commonly use social media (Pew Research Center, 2021), while older people engage in more PEBs. However, as evidenced by studies in Iran, context can change this relationship (Noubar et al., 2023; Shah et al., 2021). These same studies find that younger Iranians are more likely to purchase green products and to take action for climate mitigation.

Education. A study of the outdoor retailer REI's campaign to skip black Friday and get outside showed that Facebook users who used the associated hashtag #optoutside were more highly educated than those who didn't (Soule & Sekhon, 2022). This positive correlation of education level with PEBs is consistent in studies that consider education (Dekoninck & Schmuck, 2022; Shah et al., 2021; Zhamaliveva et al., 2023; X. Zhang & Zhong, 2020). A survey of 1105 Austrians measured a positive correlation between education level and PEI, even though education level is negatively correlated with PEB.

Gender. The relationship between gender and PEBs is not as straightforward as age or education. Some researchers find no correlation between gender and PEBs (Boulianne & Ohme, 2022; R. Han & Cheng, 2020), although both of these studies are primarily concerned with public sphere PEBs. Several studies have revealed gender differences in PEBs (Bonnici et al.,

2023; Carducci et al., 2017; De Rock & Henaff, 2023; Dekoninck & Schmuck, 2022; Soule & Sekhon, 2022). For example, Soule and Sekhon (2022) indicated that Facebook users who used the hashtag #optoutside were more likely to be female than those who didn't in their study, and De Rock and Henaff (2023) revealed that Swedish women have greener and stronger preferences than men. The same study finds that while men and women perform similarly in a public-sphere PEBs, such as voicing political support, women in this sample were far more likely than men to engage in private-sphere PEBs, such as grocery store purchases or recycling cans. There are psychological explanations for this apparent difference in how gender impacts public and private sphere PEBs (Ayala Chavez, 2024; Eiseman, 2016). One possibility is that women are more likely to engage in PEBs and outperform males in the private sphere because they do the majority of the private-sphere purchasing and work (Eiseman, 2016). Another possible factor in this difference is related to the visibility of public-sphere PEBs and the role of PEBs as status indicators (Eiseman, 2016; Soule & Sekhon, 2022).

Income. Similar to education level, researchers found that those with higher incomes participate in more PEBs than those who earn less (R. Han & Xu, 2020; Xu & Han, 2019; X. Zhang & Zhong, 2020). PEBs are costly in terms of money and time, and this strong relationship is reflected in the broader PEB literature (Grilli & Curtis, 2021).

Media exposure. Media exposure refers to the time spent engaged with media, and specifically social media and social networking sites (SNSs). Studies suggest that social media's outsized impact on PEBs originates from its ability to amplify interpersonal communication (sometimes called e-word-of-mouth or eWOM) in SNSs (R. Han & Xu, 2020; Li & Noor, 2022). Among young people in Canada, France, the U.S., and the UK, Boulianne and Ohme (2022) found that following environmental groups on social media triples the odds of participating in

marches, boycotts, and petitions. Social media use was a greater influence on Pakistani farmers' PEBs than their personal norms (Wang et al., 2020). Researchers worldwide have also found that browsing and interacting with an online community deepened environmental concern in its users (Liu & Li, 2021; J. Shen et al., 2023).

Media exposure has different effects on public and private-sphere PEBs. A study by Zhang and Li (2023) found that social media exposure had significantly higher impacts on public-sphere PEBs than private-sphere PEBs, implying that media exposure activated social norms in the users. A study of recycling behavior showed the same trend, with media exposure showing a minor influence on this private-sphere PEBs (Sujata et al., 2019).

The visibility of the PEBs is only one factor that mediates the impact of media exposure on PEBs. Factors such as an individual's level of concern, their active vs. lurker status, the media context of the country studied, and status-seeking behavior can change the impacts of media exposure on an individual's PEBs. Social media posts that encourage anti-consumption behavior have demonstrated more effectiveness the lower the environmental concern shown by the user (Soule & Sekhon, 2022), implying that the post had more significant impacts on those individuals without pre-existing high levels of environmental concern. Soule and Sekhorn's (2022) findings also contradict the idea of a social media bubble, where individuals only interact with content they already agree with.

The literature has depicted distinctions between active generators of content (15%) and lurkers (33%) on social media, with content generators having higher levels of PEI and concern (Han et al., 2018). Among U.S. survey respondents who encountered climate change information on SNS, 76% took some action on posts, liking, or sharing, while 25% of individuals reported intentions to change their personal behavior (Sofio, 2020). Birders in Hong Kong who used

SNSs were primarily motivated by hedonistic values such as status-seeking and socializing gratification but not by information-seeking and this changed the impact of media exposure (Ma et al., 2021). Due to these differences, SNS usage was a negative correlate of responsible birding behavior, whereas those few SNS users who received information-seeking gratification were the most responsible birders. There could be confounding factors such as the tendency of status-seekers to be male and narcissistic. It is possible that underlying demographics could be partially responsible for the negative correlation between status-seeking and PEBs, although several studies echo the finding that social media users who are generally seeking status display low levels of private-sphere PEBs (Eiseman, 2016; Soule & Sekhon, 2022). Finally, in countries where the media is well developed, or the environmental situation is worse, media exposure had even larger impacts on PEBs (Zhang & Zhong, 2020), indicating that media exposure is more effective when trust in the media is high and when environmental conditions are serious.

The impact of media exposure on PEBs is significant and complex. Greater media exposure generally predicts higher levels of PEBs, but several factors, such as PEB visibility, an individual's environmental concern, status-seeking behavior, lurking, and trust in media can mediate or alter that relationship (Grilli & Curtis, 2021). Campaigns that target private-sphere PEBs, individuals with low environmental concern or high status-seeking behavior may be less effective than for public-sphere PEBs, highly concerned and altruistic users (Ma et al., 2021).

Nature Connection. A person's nature connection can have profound impacts on their environmental concern and behaviors (Whitburn et al., 2020). A 2021 study found that Chinese adolescents who spent time outdoors when young were more likely to join environmental clubs, and more likely to engage in PEBs (Wu & Otsuka, 2021). Other studies suggest that spending time in nature is not the only way to develop a strong nature connection. Ng (2022) finds that

exposure to nature on SNSs correlates with PEI and PEBs. This study found that while the motivation for seeking out nature 2.0 through SNSs is informational, the relational and emotional exposure to nature online simulated nature connectedness. Another study revealed that sharing climate change information on Instagram is associated with the individual's nature connection and that nature connectedness is positively correlated with age (Zhamaliveva, et al., 2023). This is consistent with the literature on nature deficit disorder, which pointed to a dramatic decrease in nature connection in industrialized economies (Driessnack, 2009). Zhamaliveva and colleagues (2023) also discussed the use of Instagram to gain nature connection, agreeing with the findings of Ng (2022).

Efficacy.

***Self-Efficacy*.** Bandura (1977) defines self-efficacy as confidence in one's ability to complete a specific action. He further claims that self-efficacy determines whether intent becomes action better than any other factor (Bandura, 2002). This is particularly important in the context of PEBs because many studies show a resignation in the face of global environmental crises. A survey of Lithuanian citizens found that on average, respondents disagreed with the idea that their personal behavior could make a difference (Trivedi et al., 2018). Kim and Choi (2005) found that American consumers' choices were directly influenced by this efficacy, or belief in one's ability to do something, in this case, help the planet. Self-efficacy can be built in several ways, including witnessing modeled behavior, successful attempts, and positive talk (Blackmore et al., 2021). Studies suggest that SNSs such as Facebook are particularly useful for increasing self-efficacy due to the ability to share photos and experiences and offer feedback and reinforcements (Huang, 2016). For example, a 2012 study of 179 North Carolina residents found

that anticipating neighbors' negative feedback reduced interest in native landscaping (as opposed to turf grass; Peterson et al., 2012).

Collective Efficacy. Just as individuals hold beliefs about their ability to complete an action, individuals also have beliefs about the abilities of groups to complete actions. Some research finds that collective efficacy is a better predictor of PEBs than self-efficacy (Jugert et al., 2016). Bandura (2000) emphasizes that "the growing interdependency of human functioning is placing a premium on the exercise of collective agency through shared beliefs in the power to produce effects by collective action." Other studies find that collective efficacy is greatest for PEBs that are moderately difficult (Reese & Junge, 2017). These findings argue that for a very difficult PEBs, such as living plastic free, an individual doubts the ability of others to complete the PEBs, whereas for a very simple PEBs such as recycling cardboard, individuals discount their own actions as unimportant in the big scheme of things (Velasquez & LaRose, 2015). Results from previous research also indicate that self-efficacy is a precursor of collective efficacy which in turn is a predictor of PEBs (Jugert et al., 2016).

A wide array of PEBs are represented in the existing studies, from green purchasing to birdwatching, and each PEB has characteristics like visibility and difficulty that make each one unique. In addition to our knowledge of these antecedents to PEB, there is an additional body of research specifically about the use of native species in landscaping and some of the antecedents of the behavior that affect an indivudual's landscaping choices.

Native Plants

Native plants are those that existed in a specific state, continent, or ecozone before 1492 (for North America), and exotic species are those that have been introduced since that time. Exotic species can be invasive, that is, they can outcompete native species for habitat, nutrients,

and sunlight (Narango et al., 2018). North American native plants have spent millennia evolving intricate interactions with native pollinators and wildlife, creating unique relationships between those plants and the animals around them (Tallamy, 2021); however, in a typical urban and suburban setting, 78% of plants and more than 90% of the area is covered by exotic plants that may not host and feed wildlife (Tallamy, 2021). Research has found that a minimum of 70% native species is ideal for nesting bird survival (Narango et al., 2018). A native oak species, for example, is home and host to more than 500 species of moth, beetle, and butterfly, while a popular Asian species, such as the crepe myrtle, is host to only three (Tallamy, 2021). It is estimated that over the past 200 years, one in four insect species has been driven to extinction (Fonseca, 2009). Of the 1285 plant species listed as invasive in the United States, 61% are readily available for purchase from big box stores and nurseries (Beaury et al., 2021). Encouraging pro-environmental consumer behavior around ornamental plants is one part of the effort (along with more state and federal regulations on the import of these species; Early et al., 2016). Planting native species and removing exotics is a well-studied pro-environmental behavior with wide-ranging local and global impacts on wildlife, climate, and biodiversity. The collapse of the monarch butterfly population due to the loss of milkweed fields in North America to corn and soybean monocultures has drawn much media attention, exemplifying the global impacts that native plant populations can have on wildlife and biodiversity (Belsky & Joshi, 2018).

In 2017, Rodriguez and colleagues designed an educational intervention for residents of Raleigh, North Carolina. Urban and suburban property owners were asked to state their preferences for yard landscaping using 0%, 25%, 50%, and 100% native planting examples. Initially, respondents preferred the 50% native landscaping, but after these residents were

informed about the benefits of native landscaping, their responses changed significantly in the direction of more native plants. This study found that lower-income residents and homeowners preferred more native plants (than exotics, primarily grass species) in their landscaping than high-income residents, white residents, and renters (Rodriguez et al., 2017). These findings are partially contradictory to other literature, which finds that income is positively correlated with pro-environmental behaviors. In this case, high income neighborhoods may be more likely to maintain a certain well-manicured look, only obtainable with turf grass and other exotic species. This reinforces the idea that not all PEBs are the same and that the details matter.

A 2021 survey of Northwestern U.S. gardeners found that aesthetics, pollinator support, and affiliation with a native plants group were the main reasons people reported planting native plants (Anderson et al., 2021). This same study also found that a small amount of information about pollinators and their reliance on particular native plants was sufficient to change the planting intentions of regular gardeners.

Social Media's Influence on PEBs

Social networking sites (SNSs) such as Facebook have a broad audience and provide users with valuable information and social exchange. Almost two billion people use Facebook Groups monthly (TheGovLab, 2021), and Facebook is just one of several large social networking sites. The Pew Research Center for the People and the Press (2009) writes that SNSs can be communities of like-minded peers and a space in which to ask questions, provide answers, and build self-confidence, ultimately facilitating behavior changes. A study of a climate change-oriented Facebook page found that its users were more informed about climate change than those not using the page (Robelia et al., 2011). The same study found that users' PEBs increased after a month of using the Group.

A 2022 study concludes that user-generated content on social media makes up 39% of the time Americans spend consuming all media (Spangler, 2022). Further studies indicate that media consumers in both the U.S. and China trust user-generated content more than they trust traditional media (Funk, 2021; R. Han & Xu, 2020).

In general, the literature supports the role of social media in influencing PEBs (Luck & Ginanti, 2013). For example, Shah and colleagues (2021) found that increased exposure to information related to climate change on social media contributed to climate-related pro-environmental behaviors. Other studies report that social media use increases environmentally friendly purchases (Goh et al., 2013; Pittman et al., 2022). Research has also shown that sustainability-themed conversations on social media reinforce pro-environmental behaviors (Boulianne & Ohme, 2022; Sujata et al., 2019). Furthermore, instead of passively receiving messages from websites, individuals in a social media setting actively participate in online dialogue. A study of Canada, France, the UK, and the United States, found that social media is the most consistent predictor of environmental activism (Boulianne & Ohme, 2022).

There are notable exceptions, however, that cast doubt on the efficacy of social media for behavior change. In a UK-based study, a large food retailer designed traditional and social media interventions to reduce food waste (Young et al., 2018). This study found that the social media intervention was no more or less effective than traditional media or in-person interventions. A different study of environmentally friendly food purchases found that social media interventions based on self-esteem and materialism did not effectively change purchasing behavior (Hynes & Wilson, 2016). A quasi-experimental social media intervention to reduce plastic water bottle use was ineffective, except for people who already had strong pro-environmental values (Bolderdijk et al., 2013). All of these failed social media interventions have a commonality in the private-

sphere nature of the PEBs. When a behavior is conducted in private, such as food purchases, those behaviors are less likely to be influenced by social norms (Liobikienė & Poškus, 2019) and, therefore, by social media. Interestingly, private-sphere PEBs are influenceable by social media interventions by making private-sphere behavior more visible and subject to social norms through the use of badges, pictures, group memberships, and other signals (Carattini et al., 2022; Eiseman, 2016; Hoffmann et al., 2022).

Limitations. There are downsides to social media learning, such as de-skilling and misinformation (Lee et al., 2023; Santaoja, 2022). One study of a mycology-focused Facebook Group found that some Group users substituted the Group's collective knowledge for their own skill in mushroom identification, creating a "de-skilling" effect (Santaoja, 2022). The effects of social media misinformation and echo chambers were widely studied through the Covid-19 pandemic. One study found that people who got news from social media were more susceptible to Covid misinformation and disinformation than counterparts consuming traditional media news (Lee et al., 2023).

Many traditional sources of informal science learning, such as zoos, museums, and science centers, have used social media to disseminate information, and this type of social media marketing does not use the learner-centered and collaborative nature of science-based social media groups (Scheufele, 2015). There is currently no standard method for evaluating this type of learning environment. The NISE climate education network measured its digital footprint using opinion-tracking software to process a large number of posts across social media networks for virality (Scheufele, 2015). This assessment does not measure learning or behavior change directly, only virality, which is only one part of how social media networks operate to stimulate learning.

Summary

Research on PEBs and social media as a tool to encourage PEBs is multidisciplinary (Ballew et al., 2015). Empirical studies are found in the fields of technology and computer science (e.g., Hoffmann et al., 2022), marketing (e.g., Zafar et al., 2021), natural resources (e.g., Peterson et al., 2012), psychology (e.g., Shen et al., 2020), and education (e.g., Chung et al., 2020) among others. While concepts and theories may have different emphases or labels in disparate fields, the constructs remain largely the same. Pro-environmental behaviors differ in difficulty, visibility, and personal and social norms (Grilli & Curtis, 2021). Planting native plants and removing invasive exotic plants is a relatively difficult and semi-visible PEB (Anderson et al., 2021).

The wide variety of PEBs and contexts studied around the world has offered up contradictory insights into the usefulness of social media to encourage PEBs and the best practices for environmental learning in these communities. This dissertation seeks to fill a gap in our knowledge of US-based social media learning communities, which factors have the most influence, and how these Groups can increase their impact. For this study, the PEB antecedents of social media use, social norms, and both self- and collective efficacy were measured in members of US-based native plant Facebook Groups for their effects on behavior.

CHAPTER 3:

METHODS

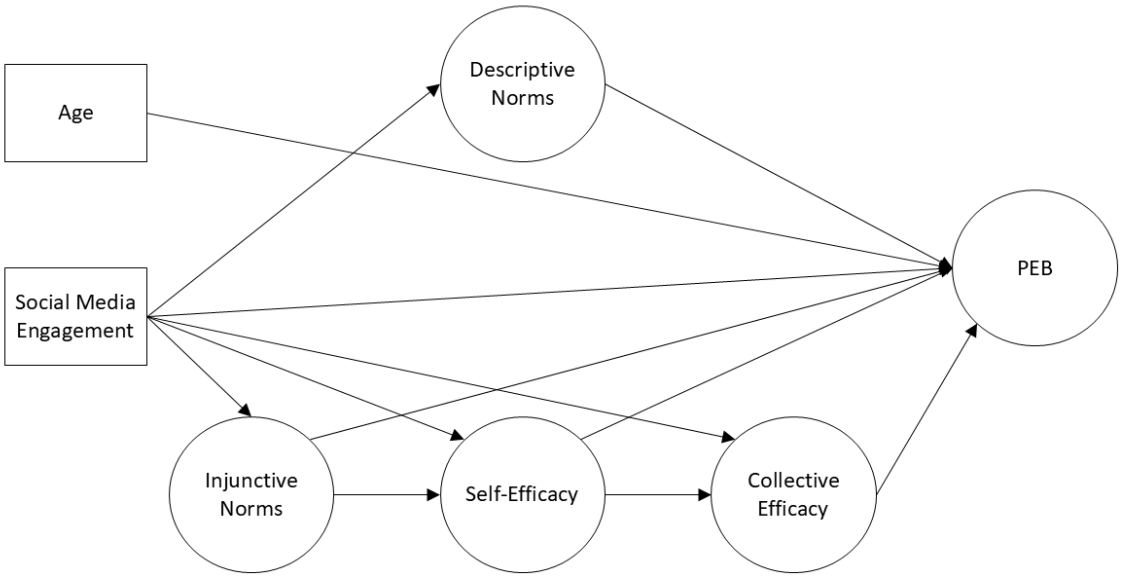
Purpose and Research Questions

The purpose of this study was to examine the factors that lead to PEBs for members of native plant-focused Facebook Groups. Specifically, the research explored how social norms, social media engagement, efficacy, age, gender, and Group rules impacted learning and PEBs in these Groups.

The conceptual model in Figure 3 adapts the Theory of Planned Behavior specifically to this study. It is not an exhaustive model of the precursors of PEBs; such a model would be prohibitively complex (Ballew et al., 2015). Recent studies worldwide have informed modifications to the model that provide possible relationships between these factors. The relationship between demographics such as age, gender, and income and social media engagement is based on research from the Pew Research Center (2021) classifying social media engagement by age, gender, and race. The relationship between demographic variables and social norms is hypothesized and explored in two recent studies of social norms as predictors of PEBs (Han et al., 2021; Hynes & Wilson, 2016).

Figure 3

Conceptual Model



This model also hypothesizes relationships between social media engagement and social norms. Based on the work of Borg (2021), this conceptual model predicts a positive correlation between social media engagement and descriptive norms and a negative correlation with injunctive norms. Moving to the right through the model, there is a predicted positive relationship between descriptive norms and PEBs and a negative predicted relationship between injunctive norms and PEBs.

Social media engagement is also hypothesized to impact both self-efficacy and collective efficacy based on the research conducted by Huang (2016) and Jugert and colleagues (2016). This research also hypothesizes that self-efficacy is a precursor of collective efficacy, so this model includes that linear relationship.

The research questions this dissertation sought to answer were:

1. What are individuals' native planting practices/PEBs and how much can users' PEBs be attributed to participation in a Facebook Group?
2. How do key factors (social norms, social media engagement, self-efficacy, collective efficacy, age, and/or gender) interact to predict individuals' PEB?
3. What types of learning outcomes result from participation in the Facebook Group and does the duration of membership impact this learning?
4. What are the differences in rules, moderation, virality, nature of the online discourse, and associated impact on promoting PEBs in three regional Facebook forums?

Research Worldview and Research Design

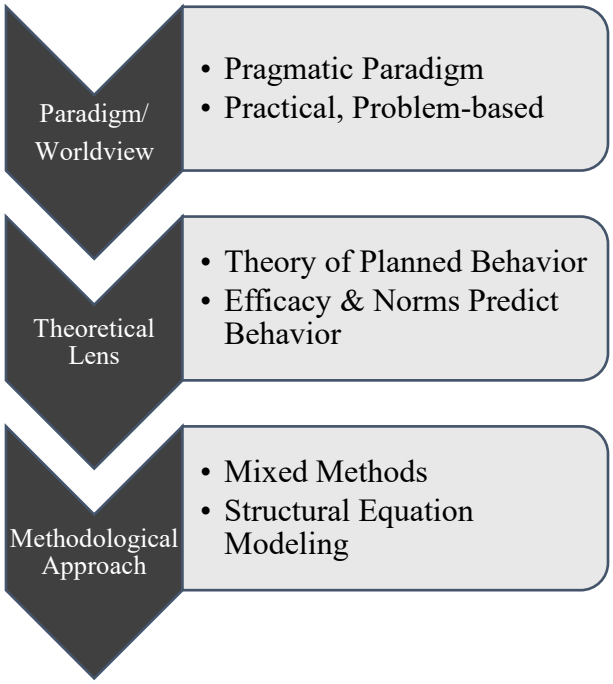
The author of this dissertation has a pragmatic worldview, which is common in mixed-methods research (Creswell & Plano Clark, 2011). The pragmatic paradigm supports research based on experience, experimentation, and action (Ormerod, 2006), and pragmatic research employs methodologies based on their usefulness for social advancement (Mills et al., 2023). The pragmatic worldview is characterized as problem-focused, mixing qualitative and quantitative data and using practical methods for the problem under scrutiny. This research focused on lifelong environmental learning and utilized a mix of methodologies to best answer the questions.

This dissertation applied these related concepts from TPB to create a structural model where PEB is the desired behavior, and factors include norms and efficacy. Figure 4 shows the hierarchy of theories that informed this work. The worldview is the most general, describing the "worldview" of the researcher, followed by the theoretical framework, and most specifically, the methodological approaches. This research used a fixed mixed methods approach, which means that the research questions are designed for qualitative and quantitative answers from the

beginning of the study (Creswell & Plano Clark, 2011). The quantitative strand of the work uses a structural equation modeling approach, which is appropriate for exploring the relationships between latent or unmeasured factors (Bollen, 1989) such as norms and efficacy.

Figure 4

Theoretical Foundation for this Dissertation



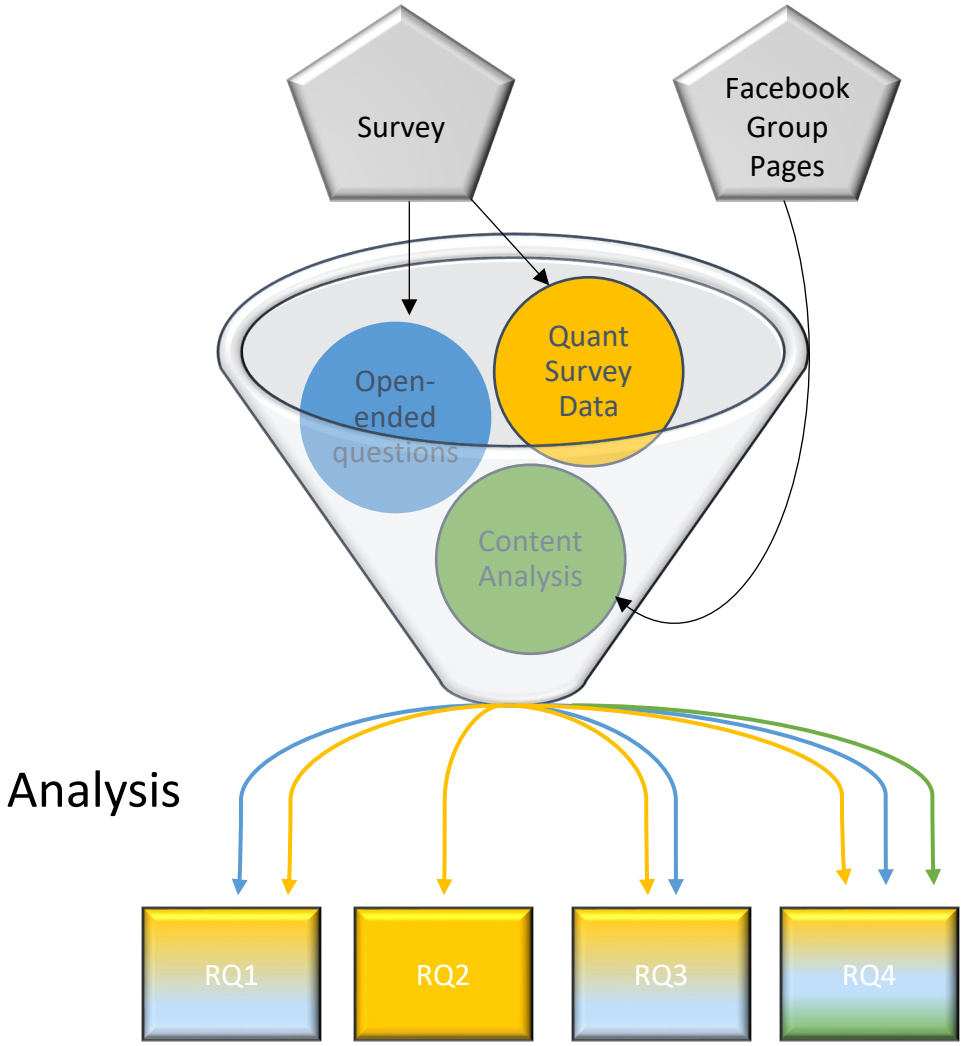
This study used a mixed methods design, represented in Figure 4, to answer the research questions posed in this paper. Mixed methods are defined as those that include both quantitative and qualitative analysis (Creswell & Plano Clark, 2011). The particular study design used in this research is also fixed and embedded. A fixed study is determined to be mixed methods at the beginning of the study, whereas an emergent mixed methods study happens in response to needs or problems during the study (Creswell & Plano Clark, 2011). Fixed mixed methods are often chosen in order to triangulate and enrich data. An embedded study describes

the overall design and prioritization of quantitative and qualitative data (Merriam & Tisdell, 2016). Embedded research is primarily either quantitative or qualitative, with the other data form added for a specific reason. Finally, mixed methods studies can be concurrent or sequential in terms of data collection. In a sequential study design, one form of data is collected first, thereby informing the collection of the other data strand (Creswell & Plano Clark, 2011).

A fixed embedded and concurrent mixed method approach was chosen for this study for a variety of reasons. Mertens (2020) argues that mixed methods are beneficial for problems in complex social or educational contexts, which aptly describes social media platforms. The author chose a mixed methods design after previous qualitative research projects on this subject highlighted the need for quantitative data to enable comparisons with similar research abroad. The embedded design with quantitative data at its center was chosen because the intended qualitative data (content analysis and two open-ended questions on a survey) was not robust enough for its own qualitative study. Instead, it was intended to triangulate the quantitative data. Triangulation is defined by Merriam (1998) as the use of multiple methods, investigators, or sources of data to confirm emerging findings. In this study, triangulation was deemed necessary because any one of the data sources used is insufficient on its own for answering the research questions, which is the purpose of the embedded mixed method. The qualitative data provides a personal and specific view of the Group and its impacts, while the quantitative data provides a larger overall view of the phenomenon. These tools resulted in three data sources, as depicted in Figure 4. The analysis combines these data with no preference for qualitative or quantitative form. Figure 5 depicts the conceptual model of relationships hypothesized in this study.

Figure 5

Embedded Mixed Methods Study design



Population, Sample, and Recruitment

Three distinct social media Groups comprised the populations for this study. These three were chosen because of their subject matter, size, and representation of different regions of the U.S. Research shows that PEBs display a range of relationships to other constructs based on factors such as visibility and difficulty. In order to limit the variables in this study, all of the chosen groups work toward the same set of PEBs. Groups were chosen from different areas of

the U.S. in order to capture a diversity of people and issues in the Groups. Additionally, the similarity of the three Groups allowed a comparison of the administration and moderation practices without other influences. The researcher requested and was granted membership in the North Carolina Native Plant Forum on December 20th, 2020, and the other Groups on February 08, 2022. The Northeast Native Plants Society is the largest of the Groups, with over 200,000 members, while the California Native Plant Society is the smallest, with 85,954 members. These sizes were chosen in order to obtain as many survey responses as possible.

Context and Participants

Participants for this study were drawn from three regionally specific gardening and native plant Facebook Groups, as described in Table 1. The researcher issued Facebook calls for participants through a post. All participants had to be 18 years old to participate. Participants recruited from Facebook filled out consent forms and completed the survey online via Qualtrics. Recruitment and data collection began on October 8th, 2024 and ended on October 18th, 2024.

Table 1

Research Participant Populations as of November 2024

Facebook Group	North Carolina Native Plant Forum (Facebook)	California Native Plant Society (Facebook)	Northeast Native Plants Society (Facebook)
Population Size	97,901	85,954	215,183
Sampling Method	Facebook post, link to Qualtrics survey		
Sample Size	407	224	777

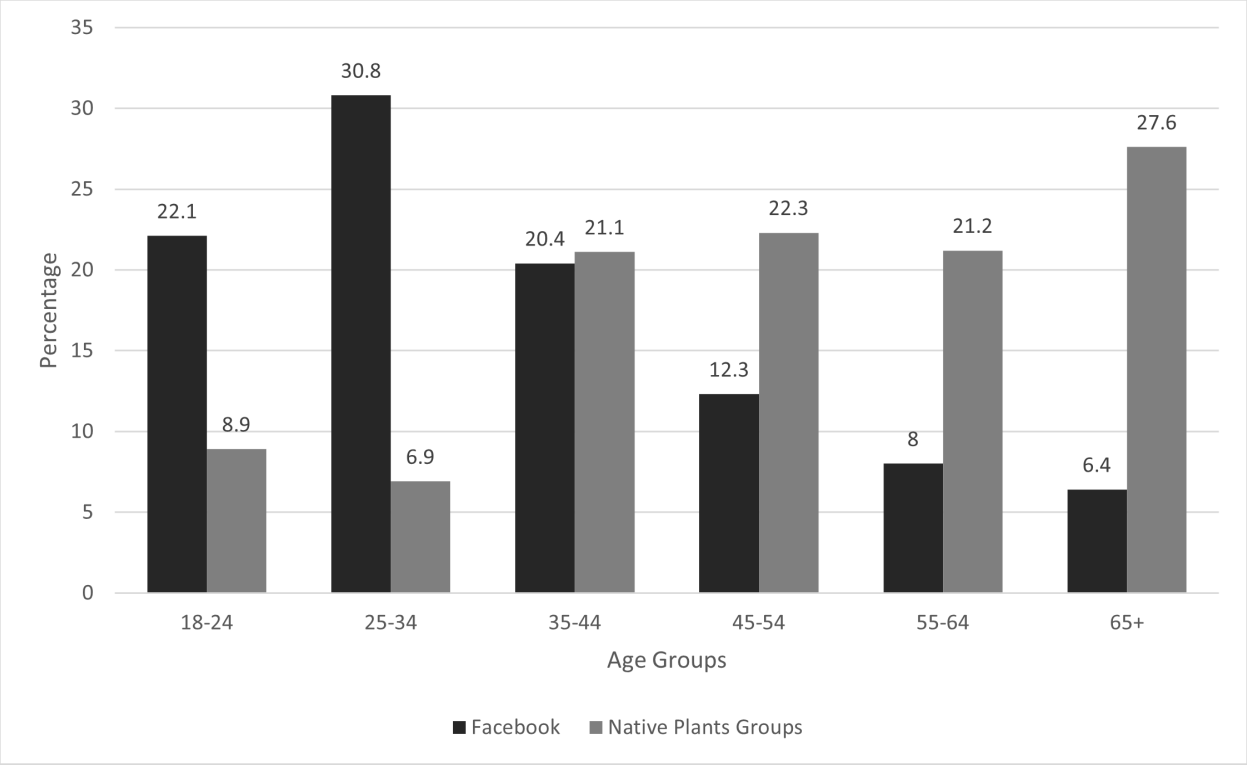
Respondent Demographics and Group Characteristics

One thousand five hundred twenty-one participants completed the survey, and 1,106 recorded their age on their most recent birthday. The average participant was 53 years of age, with a range of 18-83. Female participants (85%) outnumbered males (12%), 1,195 to 185, with 28 identifying as non-binary (2.5%). Of the participants, 89% (n = 1330) reported their race as White, 4% (n = 52) as Latino/a, 2% (n = 37) Asian, 2% (n = 26) Native American, and 1% (n = 12) Black or African American. Six participants (<1%) identified as Pacific Islanders and seven (<1%) as Middle Eastern. Two percent (n = 30) listed "other". The average reported household income is $151,618.40.

In the United States, 53.8% of Facebook users are female as compared to 85% of the participants from the three sampled Facebook Groups. The native plant-focused Groups sampled in this research are skewed significantly older, whiter, and more female than the general U.S. Facebook population. Figure 6 compares the ages of study participants with the ages of U.S. Facebook users.

Figure 6

Age Distribution of Participants and All U.S. Facebook Users.



Note. Additional Data Source: https://www.pewresearch.org/internet/fact-sheet/social-media/

Instrumentation

The researcher followed a rigorous development process to produce a reliable instrument for gathering data that was aligned with answering the research questions. A literature search was conducted for validated surveys aligned with the research questions, but none were found. Instead, a combination of validated scales from the literature and customized questions was used. The author researched previously validated scales and developed the survey between January 7, 2024, and August 12, 2024, piloted, validated, and then released the survey on October 8th, 2024. This section details the survey development and validation procedure.

Survey Development

A 28-question survey was developed, piloted, and validated in this dissertation study. The survey was developed using constructs from TPB, as shown in Figure 6. This survey examined eight latent (not directly measurable) constructs or variables, such as norm perception and efficacy, as well as observable variables such as treated acreage through self-reported participant data.

Review of Existing Surveys

Several relevant surveys already exist in the literature, although none were ideally suited for this research study. As a result, some questions and wording were utilized from existing scales and surveys to align the findings of this study with other researchers' results. Figure 6 shows the alignment of these existing scales to the survey questions and the variables being measured. For example, a widely used scale of pro-environmental behaviors was developed by Kilbourne and Pickett (2008), which includes questions regarding the frequency of various PEBs. Minton and Rose (1997) developed a survey of descriptive and injunctive norms in the field of climate change. Components of this tool were incorporated into the instrument for this study. Funk (2021) measures Facebook engagement by number of weekly visits, which was utilized in this study. Dunlap and colleagues (2000) published a validated survey of environmental beliefs, which was incorporated into the survey for this study. Finally, a scale for self-efficacy was modified from Huang (2016). Due to the complexities of pro-environmental behaviors, PEB surveys in the literature tend to be either extremely general (such as Huang's self-efficacy scale) or specific to a particular context and PEBs. This means that surveys are difficult to reuse, and each new survey must be validated to ensure it collects the correct information.

Question Pool Generation

In their book "*Scale Development*," DeVellis and Thorpe (2022) recommend developing a pool of possible questions as the second step in survey development. Modified questions from the existing surveys described above were combined with novel and specific questions to answer the research questions in this dissertation. Figure 7 shows the process of mapping components of the research questions onto possible survey items.

Figure 7

Map of Scales, Variables, and Survey Items

Research Question	Variable	Survey Items	Validated Scale Reference
#1 - What are individuals' native planting practices/PEBs and how much can users' PEBs be attributed to participation in a Facebook Group?	Social Media Engagement	I visit my Native Plant Facebook Group or see it in my Facebook feed _____ number of times per week.	Funk, 2021
	Pro-Environmental Behavior	I engage in green behaviors like recycling, reducing energy use, etc. (never, once per week… daily). How many acres of land: do you care for or manage? Have you removed exotic species from? Have you planted native species on?	Kilbourne & Pickett, 2008; Dunlap et al., 2000
#3 - What learning outcomes result from participation in the Facebook Group and does the duration of membership impact this learning?	Learning Outcomes	What is an example of something you learned in the Native Plant Group on Facebook?	Anderson et al., 2021
	Demographics and Group Membership	What was your age on your most recent birthday? What is your gender identity? What is your approximate annual household income? I describe my race/ethnicity as (check all that apply).	none
#2 - How do key factors (social norms, social media engagement, self-efficacy, collective efficacy, age, and/or gender) interact to predict individuals' PEB?	Self-Efficacy	I believe that I CAN plant native plants to increase biodiversity (agreement scale). I believe that I CAN make a difference for pollinators and biodiversity (agreement scale). Although it may cause inconvenience, I can still change my behavior to help pollinators and mitigate biodiversity loss (agreement scale).	Huang, 2016
	Collective Efficacy	I believe that together with a group of native plant enthusiasts, WE CAN plant native plants to increase biodiversity (agreement scale). I believe that together with a group of native plant enthusiasts, WE CAN make a difference for pollinators and biodiversity (agreement scale).	
	Injunctive Norms	My friends think that I should plant native plants in my landscaping. My friends think that I should avoid pesticide use. My friends think that I should replace my grass lawn with native species.	Minton & Rose, 1997
	Descriptive Norms	My friends avoid pesticide use. My friends replace their grass lawns with native species.	
	Demographics and Group Membership	What was your age on your most recent birthday? What is your gender identity? What is your approximate annual household income? I describe my race/ethnicity as (check all that apply).	none
#4 - What are the differences in rules, moderation, virality, nature of the online discourse, and associated impact on promoting PEBs in three regional Facebook forums?	Demographics and Group Membership	What was your age on your most recent birthday? What is your gender identity? What is your approximate annual household income? I describe my race/ethnicity as (check all that apply).	none

Expert Review

Once the item pool was constructed, it was reviewed by several experts, three in survey design and two in science education for wording, length, vocabulary, and format to identify and modify potentially problematic items, reduce redundancy, and limit the survey to less than 30 items or 20 minutes total. Research has revealed that survey length not only produces survey fatigue in participants but can increase item skipping and random responses (Jeong et al., 2023). Based on the expert feedback, new items were added for both efficacy and norms to ensure that each construct had three measurements. Bollen (1989) recommends three measures for each latent construct in order to find a single solution to the series of equations in a structural equation model.

Cognitive Interview

In survey design, the use of cognitive interviews is another method to understand how potential participants understand and respond to survey items – also called reliability (DeVellis & Thorpe, 2022). One cognitive interview with a gardening adult was conducted on August 29, 2024. The information emerging from the interview led to changes to three survey items and participant instructions. Negatively worded items confused the interviewee, so two efficacy measures and one norm question were changed so that no questions were negatively worded. Additionally, the participant instructions were changed for the acreage estimation to round up to one, for acreages under one to capture participants with small suburban lots.

Pilot Testing

The next step in the process of survey development was pilot field testing. This process began on September 18, 2024. The pilot survey was deployed to a gardening Facebook Group

(not one of the full study participating Groups) with more than 65,000 members. Over 200 Facebook Group users clicked an in-post survey link that redirected them to Qualtrics for IRB-approved consent documentation and to complete the survey. The goal of 200 respondents for the validation is based on advice from Bollen (1989), which recommends a minimum of 100-150 data points for confirmatory factor analysis. When 202 survey participants were recorded, the survey pilot was closed. One survey participant was removed for failing to grant consent, and 19 responses were incomplete. The 19 incomplete survey responses were retained in the dataset with missing data.

Survey Validation

Survey validity helps to determine what variable causes changes in survey responses (Taherdoost, 2016). Several types of validity can be assessed for a survey, including content validity, criterion-related validity, and construct validity (DeVellis & Thorpe, 2022). The same authors describe content validity as the extent to which survey questions represent the appropriate range of possibilities. The researcher used previously completed semi-structured interviews (Personal communication, March 2024) to ensure content validity by including the full range of answers indicated by the interview participants. For instance, previous interviewees from the North Carolina Native Plant Forum named various barriers to PEB such as cost and deer damage. The options in the survey are taken from these interviews. The researcher also ensured content validity by seeking the guidance of experts in the field for these particular variables, during the expert review process.

Other important tests of validity include criterion-related and construct validity. Researchers recommend a range of sample sizes for these tests. For a 30-item survey consisting of six factors, sample sizes between 120 and 400 are recommended (DeVellis & Thorpe, 2022).

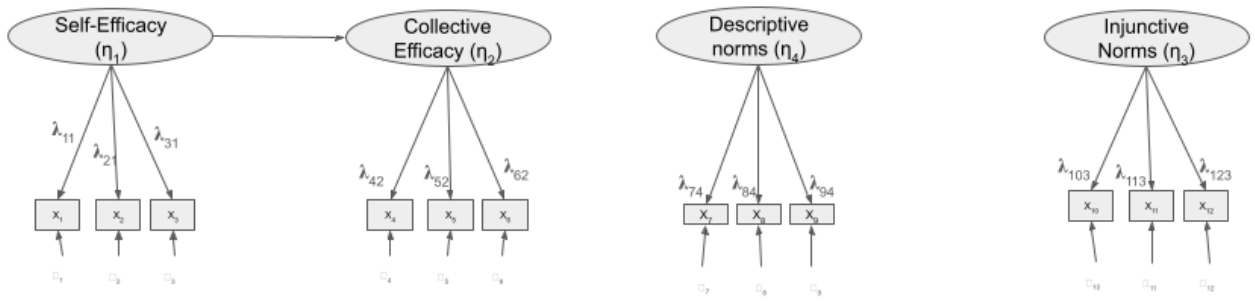
Criterion-related validity is defined as the predictive power of the survey (DeVellis & Thorpe, 2022), while construct validity measures the relationships between variables. In this case, the two validity measures report how well survey items predict native planting and how the various factors relate to each other. Pilot data validated the survey through this factor analysis using Mplus software. A measurement model of the various survey constructs is included in Figure 8.

A confirmatory factor analysis revealed the degree of co-variance among the items and how well each predicts its corresponding latent construct. Common factor analysis was used to reduce the dataset to fewer latent variables (Keith, 2019). Confirmatory factor analysis is also used when the studied factors probably do not represent all of the variance in native planting.

Once data collection was completed (over 200 responses to the pilot survey) the data were cleaned to remove responses without consent for data usage or with zero responses (incomplete survey). The remaining dataset was comprised of 169 responses, still within the recommended sample size for confirmatory factor analysis (DeVellis & Thorpe, 2022). The measurement model in Figure 8 shows the model as inputted into the Mplus software. Model identification is the process of determining whether the series of structural equations used in the model is mathematically solvable using the known parameters of the data and the model (Bollen, 1989). The measurement model was identified using both the t-rule (known model parameters must outnumber the unknown parameters), and the recursive rule (that measurement error is uncorrelated with explanatory variables; Bollen, 1989). The t-rule is necessary but insufficient on its own for identification, while the recursive rule is optional, but sufficient for model identification.

Figure 8

Measurement Model for Survey Validation



The initial model's (Val1) results reflected a fair overall fit to the data (χ^2/df = 166.5/49). Table 2 shows model fit indices for the initial model and various model adjustments. The first modification was to release the theoretical relationship between self-efficacy and collective efficacy to test whether this hypothesis was causing the data misfit. However, removing that relationship worsened model fit instead of improving it. Modification indices from the Mplus analysis pointed to issues in the 12 survey questions regarding social norms and efficacy. The model Val3a, which drops questions x4 and x9 shows an acceptable fit to the data. The Val3a factor loadings ranged from .886 to 1.637, exceeding the 0.5 threshold, and the composite reliability for all factors exceeded 0.9 (0.96, 0.96, 0.93, 0.91), demonstrating discriminant validity. The Mplus validation output file is included as Appendix B.

Table 2

Model Modifications and Measures of Fit

Model	Description	RMSEA	TLI	CFI	chi^2/df
Val1	A priori measurement model (Fig. 7)	.123	.806	.856	166.5/49
Val1a	Drop question x2 from self-efficacy	.125	.799	.853	138.2/40
Val3	Drop question x4 from collective efficacy	.095	.888	.918	97.35/40
Val3a	**Drop questions x4 and x9** from collective efficacy and descriptive norms	**.069**	**.942**	**.960**	**54.2/31**

Data Collection

Survey Data

The finalized survey was deployed using Qualtrics to three similar regional native plant-focused Facebook Groups (The North Carolina Native Plant Forum, the Northeast Native Plant Society, and the California Native Plant Society), each with over 80,000 members. On October 8, 2024, a recruitment post was made in each Facebook Group that introduced the researcher and asked for anonymous volunteers to complete a survey about their native plant landscaping and use of Facebook Groups. Responses were collected until at least 400 respondents were received from each of the three Groups. A total of 1,521 responses were collected between October 8 and October 18, 2024.

In the survey, participants were asked about their general PEB habits, such as recycling, reducing energy use, etc., in addition to asking how many acres respondents had treated by either removing exotic species or planting native species. The number of acres used is a percentage of the participant's total available acreage in order to control for differing lot sizes. The final survey question is open-ended and asks respondents to describe any PEB that can be attributed to membership in their Facebook Group. Participants were also asked to agree or disagree with a series of six normative statements as seen in Figure 6 to measure descriptive and injunctive norm perception related to native plants.

Social Media Content

In addition to the survey, content from three Facebook gardening Groups was collected. The North Carolina Native Plant Forum, the California Native Plant Society, and the Northeast Native Plant Society Facebook Groups were each sampled for a period of two to three days beginning September 29, 2024, and proceeding until 50 posts were sampled from each Group. Posts and the first five subsequent comments, plus all likes and shares, were recorded during the week in a Google Sheet spreadsheet. This sampling continued for 2-3 days, resulting in 150 posts with comments. Posts were first sorted by date in sampling content from the Facebook pages. Each post was then viewed with all comments so that the sample would be representative instead of using Facebook's "most relevant" posts, which is the default.

Data Analysis

Structural Equation Modeling

Structural equation modeling is helpful in the interpretation of complex relationships with more than one dependent variable (Hair et al., 2021). Research question 2 asks how these antecedents of PEBs interact to predict PEB. Structural equation modeling is preferable in these

conditions because it accommodates measurement error in the survey results. SEMs using a maximum likelihood (ML) estimator are the most common for standard SEMs (Keith, 2019). The ML estimator uses the specified model and dataset to estimate the most likely explanation for the observed data iteratively (Bollen, 1989). ML estimation is widely used because, among other properties, it works well with large sample sizes and can accommodate missing data, as in unanswered survey questions. This study used a relatively large data set with missing data, and for these reasons, ML-SEM was used to estimate the theoretical model of factors in native planting. The analysis was performed using the Mplus statistical platform, resulting in a theoretical model that included the relevant latent and observable factors from the survey data.

Missing Data. Seven percent of the survey responses were left unanswered, primarily in income and acreage (n=240). There are several ways to treat missing data in structural equation modeling, including listwise deletion, multiple imputation, and maximum likelihood (Bollen, 1989). This model employs the Mplus default maximum likelihood equations to estimate missing data. Running the model with listwise deletion (χ^2 = 321.2, df = 64, CFI =.974, TLI = .970) or multiple imputations (χ^2 = 319.7, df = 64, CFI =.980, TLI = .973) did not significantly change the model's output.

Model Fit. This study employed the maximum likelihood (ML) fitting function, which is the most commonly used estimator in SEM (Bollen, 1989). All SEM estimators compare covariances of the observed variables to the model structure, and the ML estimator uses an iterative process to minimize the F_{ML} fitting function. Table 3 shows the various model respecifications explored and the model fit estimators associated with each respecification. The theoretically derived a priori model showed a fair fit to the model. Allowing the error terms for injunctive and descriptive norms to covary (due to the similar wording in the survey) increased

the model fit (respecification PEBS1a). The "barriers" variable showed a positive correlation with PEBs, and removing that variable also improved model fit. In respecification PEBS2, self-efficacy was allowed to covary with both norms variables. The final respecified model, PEBS2c, shows a good fit to the data (χ^2 = 317.4, df = 64, CFI =.981, TLI = .973).

Table 3

SEM Model Respecification

Respecification	Description	Chi-Square/df	CFI	TLI
PEBs 1	A priori	4170/78	.842	.789
PEBS1a	Let injunctive norm and descriptive norm errors correlate	1822/77	.932	.909
PEBS1b	Remove barriers variable	1777/66	.933	.908
PEBS1c	Add Income variable	1821/72	.847	.910
PEBS2	Add covariance with norms and add self-efficacy link to descriptive norms and injunctive norms	608/75	.979	.971
PEBS2a	Remove PEB measure 1	597/63	.979	.970
PEBS2c	No Barriers, leave in PEB measure 1	317.4/64	.981	.973

Open-Ended Items. The survey contained two open-ended questions resulting in 2,851 short answer responses. These data were used to answer both research question one, which asks about PEBs and their attribution to Facebook Group membership, and research question three, which asks about learning outcomes. Two researchers coded ten percent of those responses (285) using Atlas.ti software. A first round of coding was open in order to capture the answers of each participant. The codebook is included as Figure 9.

Figure 9

Open-Ended Questions Codebook

Category	Code	Comment
Social Learning	inspiration	Gained inspiration
	community	learned that so many others care about the same thing. Also, learned that people can't ID plants, or learned that people are mean
	educating others	acted to educate community members through conversations, show gardens and events
	share events	took action to share events in Group
	misinformation	Mentions misinformation as a barrier to learning
	swaps	learned about or participated in plant sales or swaps.
Skills Development	erosion control	learned about erosion control methods and plantings
	herbicide use	learned about benefits/dangers or methods for pesticide and herbicide application
	propagation	Learned about native plant propagation including winter sowing, splitting, rooting, collecting seeds etc. OR began propagating plants
	disease	learned about aster yellows or another plant disease
	leave leaves	Learned about insect lifecycles and leave the leaves philosophy OR Changed their practice to leaving leaves and stems over the winter
	maintenance	Learned about how to maintain healthy native plants, as in watering, shade, soil.
Awareness/ Knowledge	ID	Learned to ID plants
	nativity	Learned about the meaning of "native", cultivars, nativars, learned which things were native, which were not
	new species	Learned about new species of native plants
	plant niche	Learned about plant niches, soil and moisture tolerances, companion planting and specific species interactions. Often state "found out which plants will grow in my shady yard in X place.
	awareness	A general awareness of what native plants are and how they are beneficial
	ecological benefits	Learned about the ecological benefits of natives or the ecological bads associated with exotics
Pro-Environmental Behaviors	native garden	Planted native plants in yard
	shade garden	Planted a native shade garden
	exotic replacement	learned about removing exotics, replacements for exotics OR Has replaced exotics with natives in their yard
	pollinator garden	Planted pollinator plants in yard
	conservation	helped conserve rare species
Resources	resources	Learned about other resources for learning, OR shared those resources
	suppliers	learned about suppliers of native plants
None	none	learned nothing or took no action

An example of the coding process is included in Table 4. The first question asked the participant to explain what they had learned from being a member of their native plants Facebook Group. Participant #8 reported learning how to determine nativity from Facebook Groups. The original code of nativity in the second round of coding was combined with ecological benefits, ID, new species and plant niche to form a "Plant info" category. For the same question, participant #1151 reports learning the "leave the leaves" ethic and other ecological benefits of native plants. These both also fall into the "Plant info" category. Other categories include "skills" such as propagation, herbicide use and erosion control, and a "social" category which includes codes such as inspiration, plant swaps, and misinformation.

The second question asked participants to identify any PEB they have completed on their property that can be attributed to their Facebook Group participation. Participant #8 replaced exotic species, and this code remains in its own category through the rounds of coding. Participant #1151 reported building a native pollinator garden. These codes (plus shade garden) collapse to the "native garden" category. Each response was assigned one or two codes, and the two coders had an initial interrater agreement of 78%. This was calculated based on the number of agreements and disagreements in the initial and second-round coding processes. Disagreements were discussed and resolved in each case resulting in 100% agreement.

Table 4

Open-ended Answer Coding Process

Participant #	Question	Quote	Initial Code	Final Code
8	Learn	How to tell the difference between a native and non-native version of a plant	Nativity	Plant info
	PEB	I recently replaced a bank of invasives	Exotic replacement	Exotic replacement
1151	Learn	I've learned more about which pollinators benefit from which specific native plants. I've learned that bees overwinter inside stalks of native flowers, so I have stopped cutting back the stalks in the fall.	Leave leaves Ecological benefits	Plant info
	PEB	We built a circular butterfly garden during Covid. At the time, we planted common landscaping plants. Since then, we have slowly replaced them with native plants. We are already seeing an increase in the number and diversity of birds and pollinators in our yard. And more birds has meant less invasive insect pests in our veggie garden.	Pollinator garden Native garden	Native garden

Content Analysis. Data from the Facebook Pages themselves were used to address research question 4, which asks how group differences in discourse, moderation, rules and virality impact the PEBs and learning outcomes. Each post and comment sampled from the Facebook Forums was analyzed for knowledge seeking, knowledge sharing, and social interactions, characterizing the discourse and learning on the forums (LCANC, 2019). Two coders used a priori codes modified from the codebook developed for Reddit analysis by Haythornthwaite and colleagues (2018), shown in Table 5 to classify posts into categories and by

virality, as in the example in Figure 9. A second coder independently coded 10% of the sampled posts and comments, and the simple interrater agreement was 89%. Each disagreement was discussed between coders until agreement was reached on all codes. One example comes from a post featuring a photo of a greater fringed gentian.

Table 5

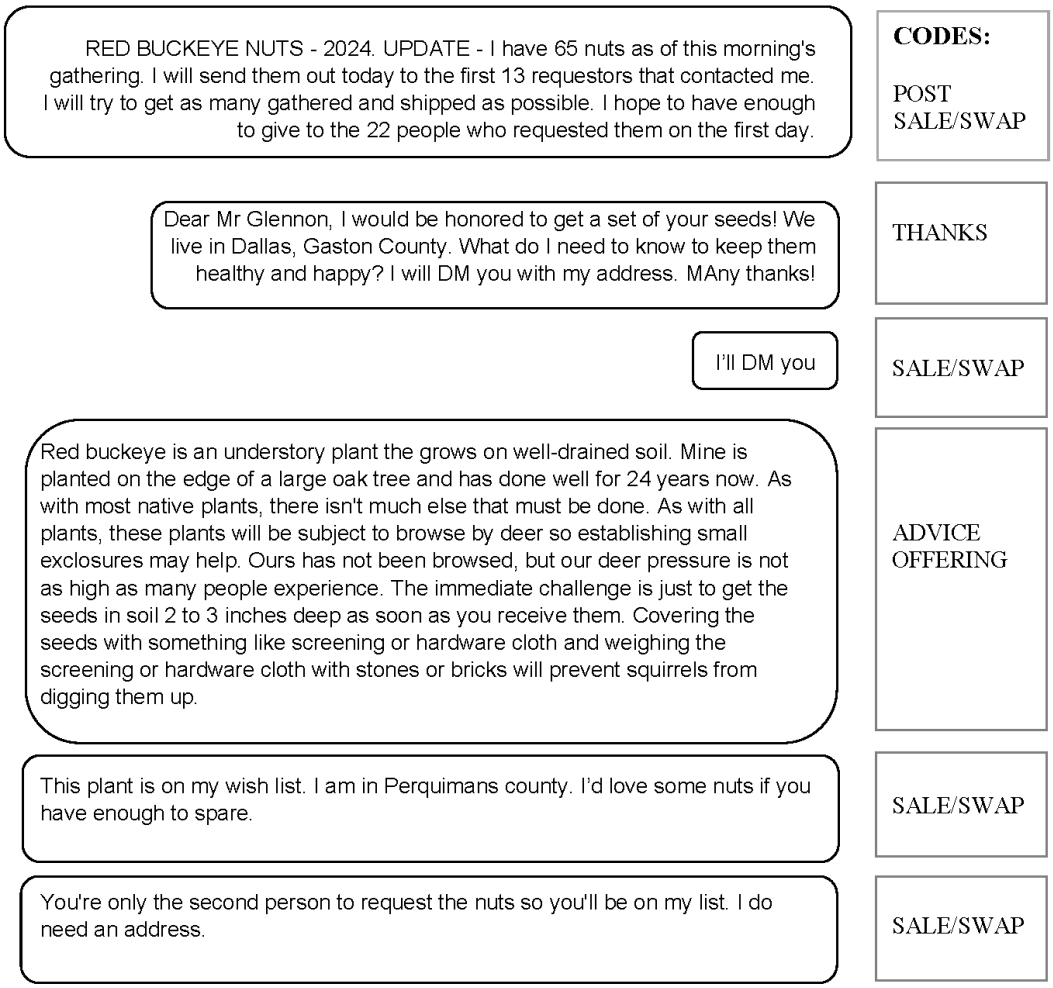
Codebook for Content Analysis of Facebook Page Discussions

	Content Analysis Codebook		
Category	**Code**	**Description**	**Comment/Examples**
Information Request	adviceR	Advice Request	Asking for advice other than plant ID
	IDR	ID Request	"What is this?" Sometimes the poster doesn't ask an actual question, but posts a photo with no ID, this is an ID ask.
Information Offer	profile	Plant profile	a post that profiles a single plant, most often with latin name and lots of info
	adviceO	non-ID advice offering	offering advice other than a plant ID. "Move the flowers now", "this tree will be fine", "you could put asters in this area."
	IDA	ID guess	maybe it's "this", "a better picture would help.", "Looks like *this* to me."
	sale	plant sale	advertises a plant or seed sale or swap. Also includes casual seed or plant swapping, gifting, selling.
	event	other event	advertising an event, not a plant sale. Workshops, conferences, work days etc.
Social Interactions	picture	Pretty pictures	"I took this amazing plant photo!"
	disagree	elaboration/disagreement with comment	a comment is elaborating or disagreeing with another poster
	agree	agreement with comment	heart emojis, "yes!", "me too!"
	awe	expressing awe, joy, appreciation	"I love this plant!", "What a beatiful picture!" This is different from agreement because it doesn't reference the previous post.
	thanks	expressing thanks	"Thank you for posting!", "Thank you for doing this!"
	norms	describing norms	"somebody yelled at me for doing x.", "My neighbors hate my yard", etc.
	personal	personal experience share	"Me too! Here's my experience", or "here's my pollinator garden one year later!"
	barrier	describing barriers to PEBs	Any description of hardship, removing exotics, finding suppliers, HOA infractions etc.

Four of the comments on the post were unanimously coded for awe, personal stories, and disagreement, however, comment four reads “maybe they do look cool”. The two coders disagreed as to whether this was awe or disagreement with the previous comment. After review, both coders agreed that awe was the probable intent. The author coded the remaining content based on these agreements. Each post with its comments and virality statistics was loaded into Atlas.ti software and each post and comment were given a single code that best described its intent. Atlas.ti analysis included coding and co-occurrence analysis. Figure 10 shows an example of a single post with codings. Additional codes were added based on the author’s previous work analyzing these types of posts (Harold & Johnson, 2024 in review).

Figure 10

Facebook Social Media Post - Content Coding Example



Ethics

Working with social media data is fraught with ethical considerations. The participants were drawn from public Facebook Groups; everything posted there, including identifying information, is public and available for anyone to see. Under these circumstances, few rules exist to protect personal information. However, studies show that Facebook users generally have a poor understanding of privacy and data issues surrounding their platform use (Zhang et al., 2013). All user data for this paper have been anonymized using Qualtrics. The risk to any of

these participants is extremely low, but caution was exercised because of the limited ability of participants to consent to this kind of public data collection.

This research was initially approved by the Institutional Review Board (IRB) at North Carolina State University on 3/12/2023, with a modification on 8/5/2024 to include the collection of the quantitative survey data and content from the Facebook Groups. The IRB approves and reviews ethics in all human subjects research to protect the rights of research participants.

CHAPTER 4:

FINDINGS

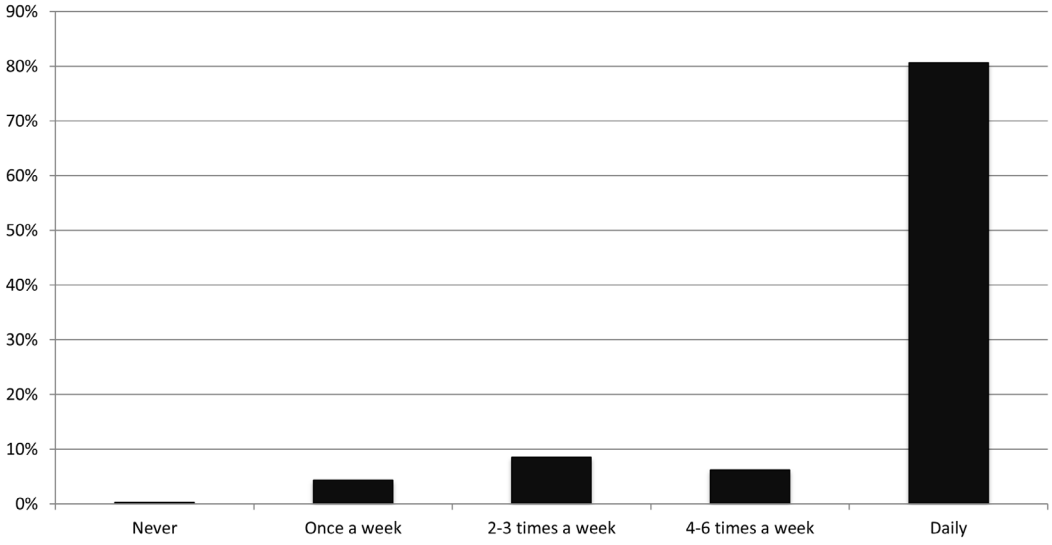
This section is organized by research question. The various sources of data are combined for analysis.

Research Question #1: What are individuals' native planting practices/PEBs, and how much can be attributed to participating in one of the subject Facebook Groups??

1,399 participants characterized their daily/weekly PEBs, and more than 80% reported carrying out these activities (recycling, plastic reduction) on a daily basis. Figure 11 shows the distribution of answers from the survey, and Figure 12 shows the answers from the open-ended survey question.

Figure 11

Self-reported PEBs Frequency



Respondents said that as a direct result of their participation in a native plants Facebook Group they had removed exotic invasive species from 7,373 acres collectively and planted 6,198 acres with native species. On average, participants reported that more than 90% of their property has been treated.

There were 1,174 participants who responded to the open-ended survey question that asked individuals to describe their native planting projects inspired by or helped by their

Facebook Group. Figure 12 shows that while 83% of Group participants report PEBs (planting native plants and removing exotics) attributable to Group membership, 164 respondents (17%) reported their participation in a native plants-based Facebook Group did not contribute to any PEBs. Participant #211 wrote:

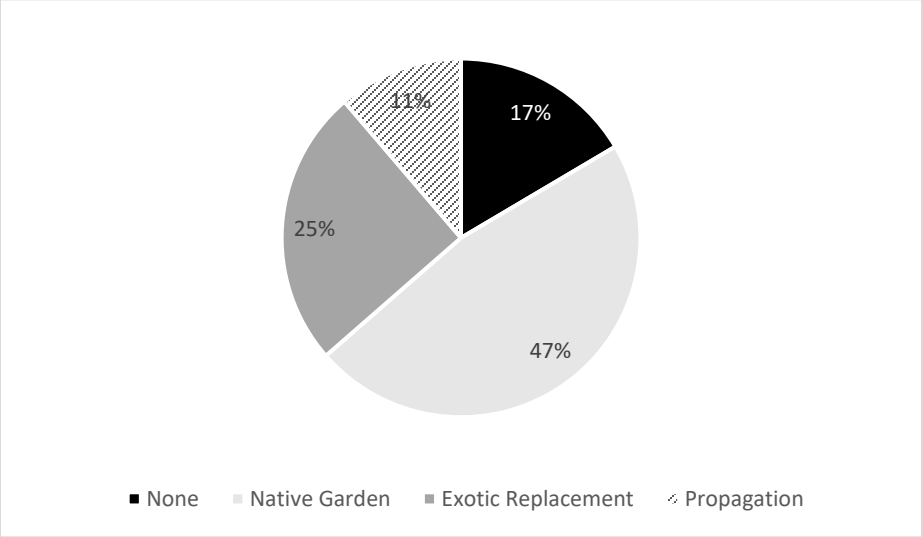
None. I'd say more that any projects I've initiated have been done based on research I've done on my own, and anything I've seen on Facebook has been coincidental. I don't find the native plant group particularly helpful because it is mostly people asking for plant identification.

Others indicated that PEBs were possible, "none yet – too new to the group" (participant #278), while others said it was not possible, such as participant #340, who answered "N/A. As a renter I don't feel I have much agency here."

Figure 12 shows what kinds of PEBs participants attributed to their Group membership. There were 234 people (47%) who pointed to a native or pollinator garden attributable to their Facebook Group membership. One participant pointed to "converting part of my lawn to a native bed" (participant #592). Participant #494 mentioned the "design of a gravel courtyard with native plants, understory plantings for a mature oak, and design of a birdbath area." Participant #459 "just redesigned [their] side yard to be my native plant garden-got ideas about what and where to plant." An additional 362 respondents (36%) listed the removal of exotic invasive species or native species propagation as the result of Group participation. One participant said, "I have removed invasive roses and honeysuckles" (Participant #282). Another respondent listed the "propagation of American beautyberry, both cuttings and seed" (Participant #209).

Figure 12

Pro-environmental Behaviors Attributed to Facebook Group Participation



Research Question #2: How do key factors (social norms, social media engagement, self-efficacy, collective efficacy, age, and gender) interact to predict individuals' PEB?

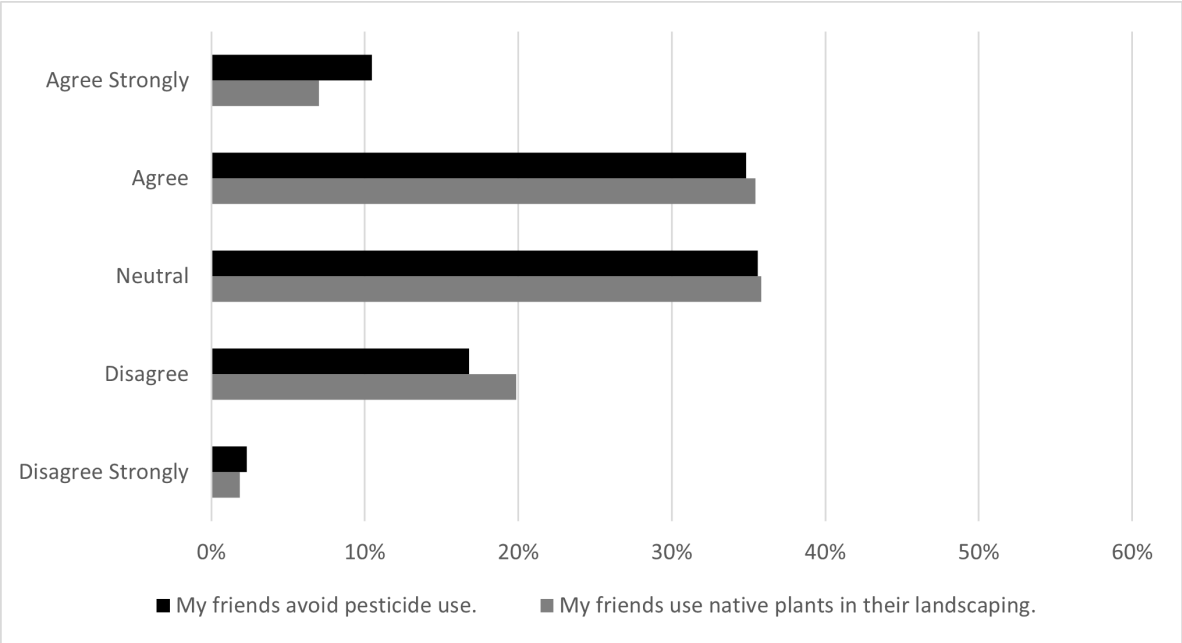
These results are organized by factor, beginning with social norms. The Mplus model outputs for the SEM model and the groups analyses are included in Appendix B.

Subjective and Injunctive Norms

There were 1,294 (85%) respondents who answered questions about their social norm perceptions. Figure 13 shows how strongly participants agreed with descriptive (first graph) and injunctive normative statements (second graph). The overall mean level of agreement for all statements was 3.34 (0.56 standard deviation), with 'neutral' being 3 and 'agree' being 4. The subgroups of descriptive and injunctive norms have very similar means: 3.37 (0.49 standard deviation) and 3.30 (0.55 standard deviation), respectively.

Figure 13

Agreement with Normative Statements



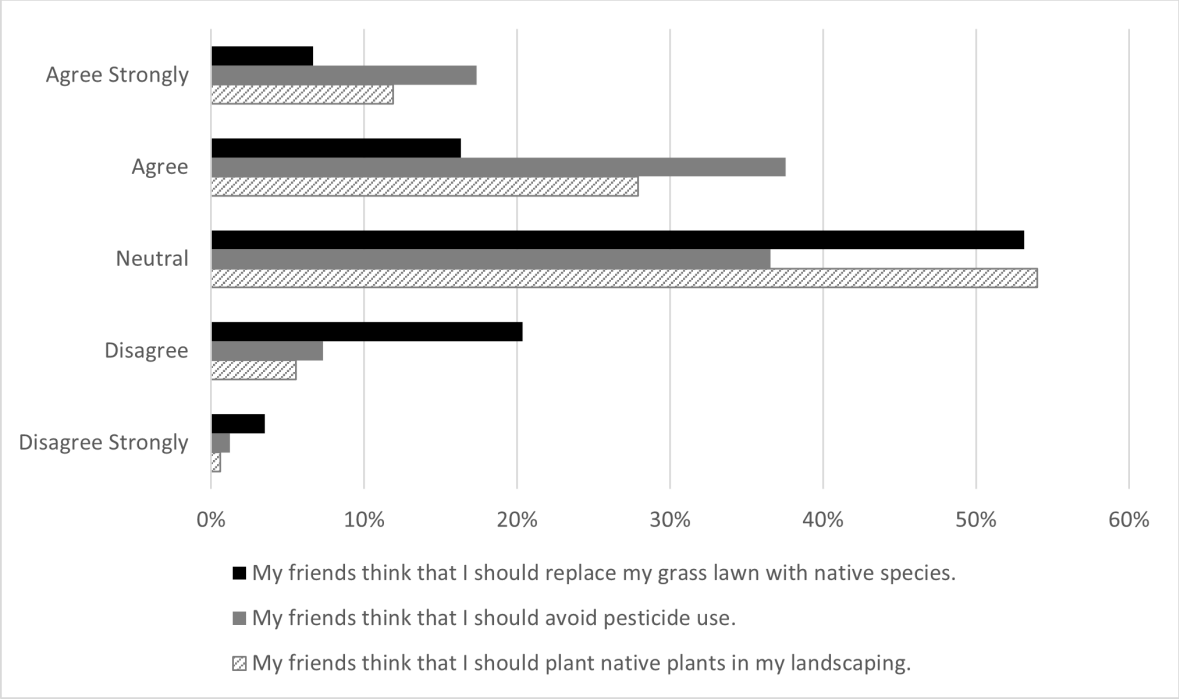
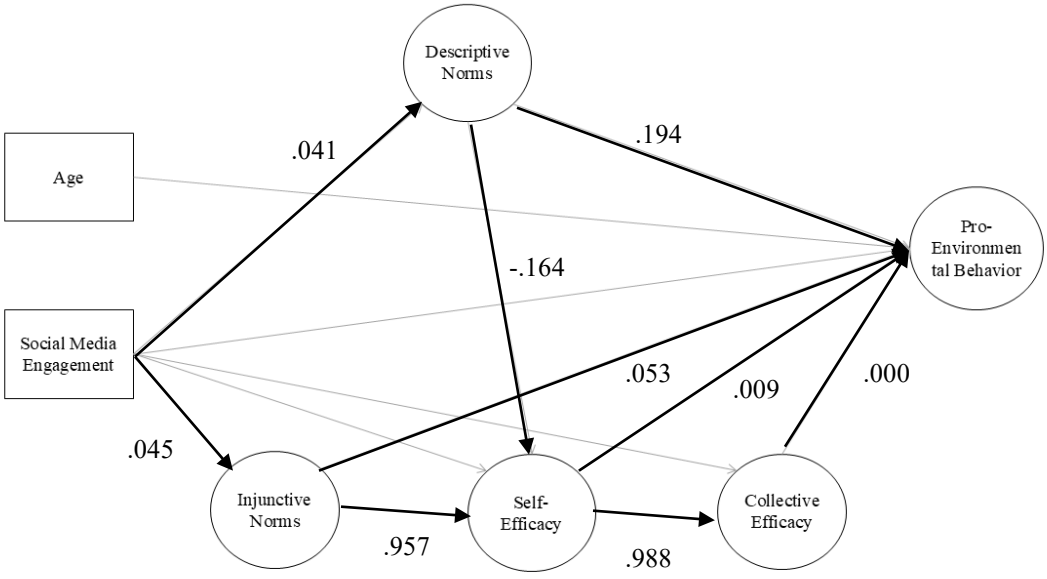


Figure 14 shows the impacts of social norms in the SEM. Social media engagement predicts agreement with descriptive norm statements ɣ= .041, meaning that for each additional 24 weekly visits to Facebook, agreement with descriptive norms increases by 1 Likert scale unit, moving from 'neutral' to 'agree' or from 'agree' to 'strongly agree'. Similarly, injunctive norms are predicted by social media engagement with a coefficient of ɣ= .045. In this case, an additional 22 weekly visits to Facebook leads to a one-unit increase in agreement with injunctive norm statements. The SEM explains 12% of the variability in descriptive norms (R^2 = .117, p< .001) and 14% of variability in injunctive norms (R^2 = .139, p< .001).

Figure 14

Norms in the SEM



Note. Unstandardized direct effects only. All values are statistically significant at the p < .05 level.

Descriptive norms and injunctive norms also have different relationships with efficacy. Descriptive norms correlate negatively with self-efficacy (β=-.164, $p<.01$), whereas injunctive norms are strongly positively correlated with self-efficacy (β=.957, $p<.01$).

Indirect Effects, and Mediation

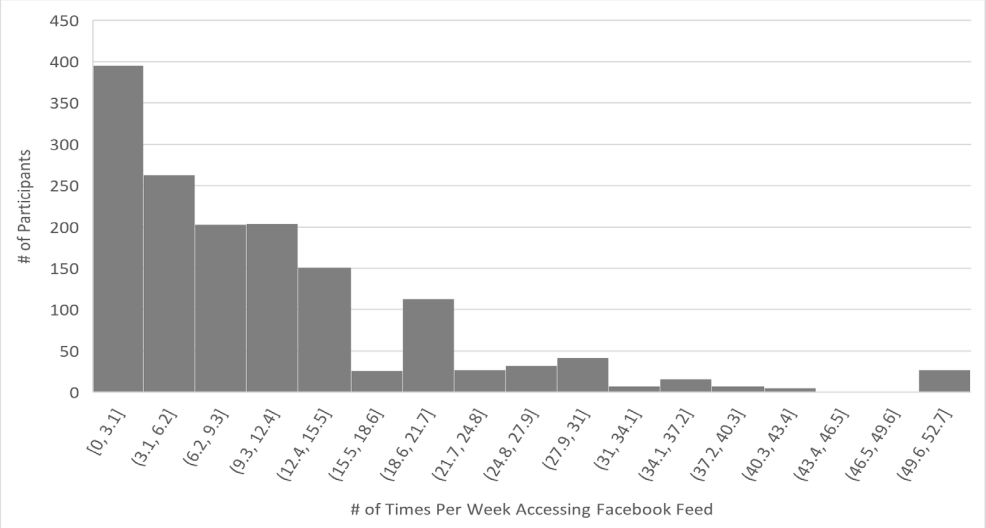
In addition to the direct effects, social norm perception indirectly affects pro-environmental behavior. These indirect effects are mediated by self- and collective efficacy. Descriptive norms have a lower total effect (.106) than direct effect (.194) due to the negative indirect effects (-.088). Injunctive norms have a stronger ability to predict pro-environmental behavior with total effects equal to 0.572 which includes .053 in direct effects and .519 in indirect effects. The indirect effects are mediated by self- and collective efficacy.

Social Media Engagement

Social media engagement is measured here as the number of times per week that a participant logs in to their Facebook Feed, which is how Facebook measures its user engagement (Moretto et al., 2022). The survey participants were asked how many times per week they logged into their Facebook feeds. The average was 10.23 times per week with a range from 0 – 52. The distribution of answers is shown in Figure 15.

Figure 15

Social Media Engagement Among Participants



SEM

Age and social media engagement show a small but significant positive correlation (.082, p<.001), meaning that for every standard deviation increase in age, there is a 0.08 standard deviation increase in social media engagement. This pattern is made more complex by opposite patterns in men and women in the sample.

Direct Effects, Indirect Effects, and Mediation

Social Media Engagement significantly positively relates both descriptive (.342, p<.001) and injunctive (.373, p<.001) norm perception. It also significantly positively correlates with self-efficacy (.097, p<.001). The weak positive correlation with collective efficacy was not significant (.002, p=.817). Engagement varied significantly and positively with age (.082, p<.005) and had a small and non-significant direct effect on PEBs (.048, p=.255).

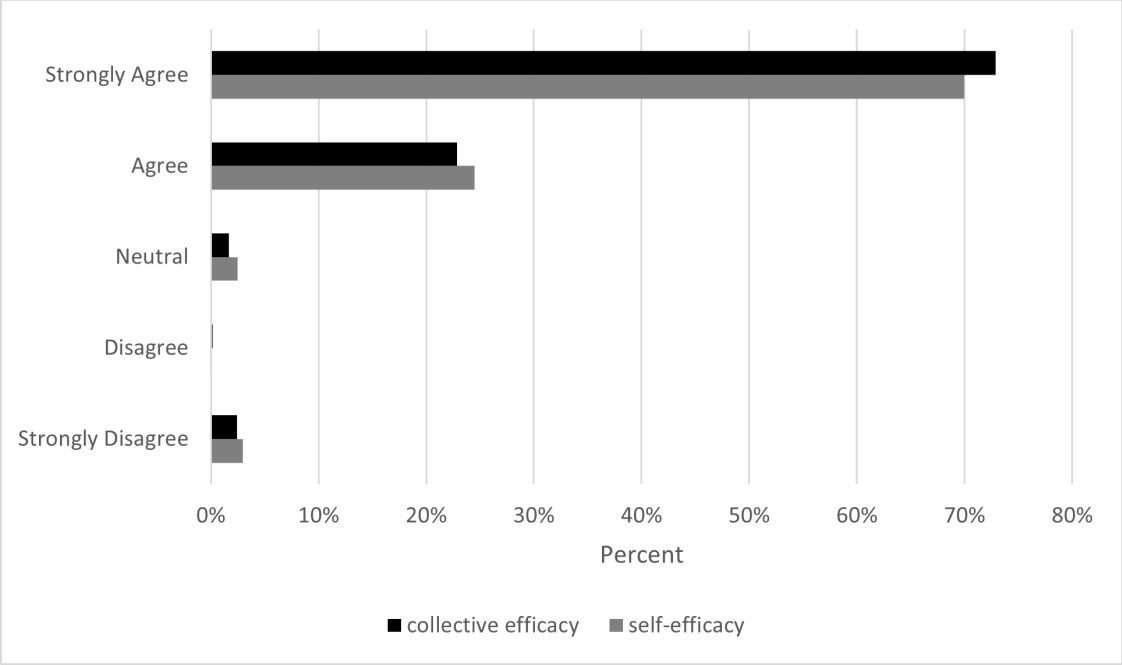
Social Media Engagement also has indirect effects through descriptive and injunctive norms, self, and collective efficacy. The combined total effect (.415) is equal to the direct effect (.048) + the indirect effects (0.367).

Efficacy

Efficacy means perceived behavioral control, or how much confidence and individual (or group) has for completing a task. When asked about their self-efficacy and collective efficacy for removing exotic species and planting native species, 1,320 responses were given for each of the five questions for each construct. The average results for self-efficacy and collective efficacy are shown in Figure 16. Seventy percent of respondents indicated strong agreement with perceived self-efficacy for planting natives and removing exotic plants, and this was even greater for collective efficacy (73%). When asked about their self-efficacy and collective efficacy for removing exotic species and planting native species, 1,320 responses were given for each of the five questions. The average results for self-efficacy and collective efficacy are shown in Figure 15. Seventy percent of respondents indicated strong agreement with perceived self-efficacy for planting natives and removing exotic plants, and this was even greater for collective efficacy (73%). These results reflect a high degree of confidence in these members' ability to complete PEBs.

Figure 16

Agreement with Efficacy Statements



Note. Percentages are averaged over two (collective efficacy) and three (self-efficacy) questions.

Self-efficacy and collective efficacy are latent variables (they cannot be directly measured) in the structural equation model, and the two variables co-vary closely with a β value of .988. Figure 13 shows the unstandardized direct effects of self- and collective efficacy in the SEM model. Social media engagement positively predicts self-efficacy (ɣ=.012). Injunctive norms predict self-efficacy with a β of .969, while descriptive social norms have a weaker and negative relationship with self-efficacy (β=-.164). Self-efficacy is the most powerful modeled predictor of native planting with ʎ=.508, while the direct modeled effects of collective efficacy are weaker (ʎ=.027).

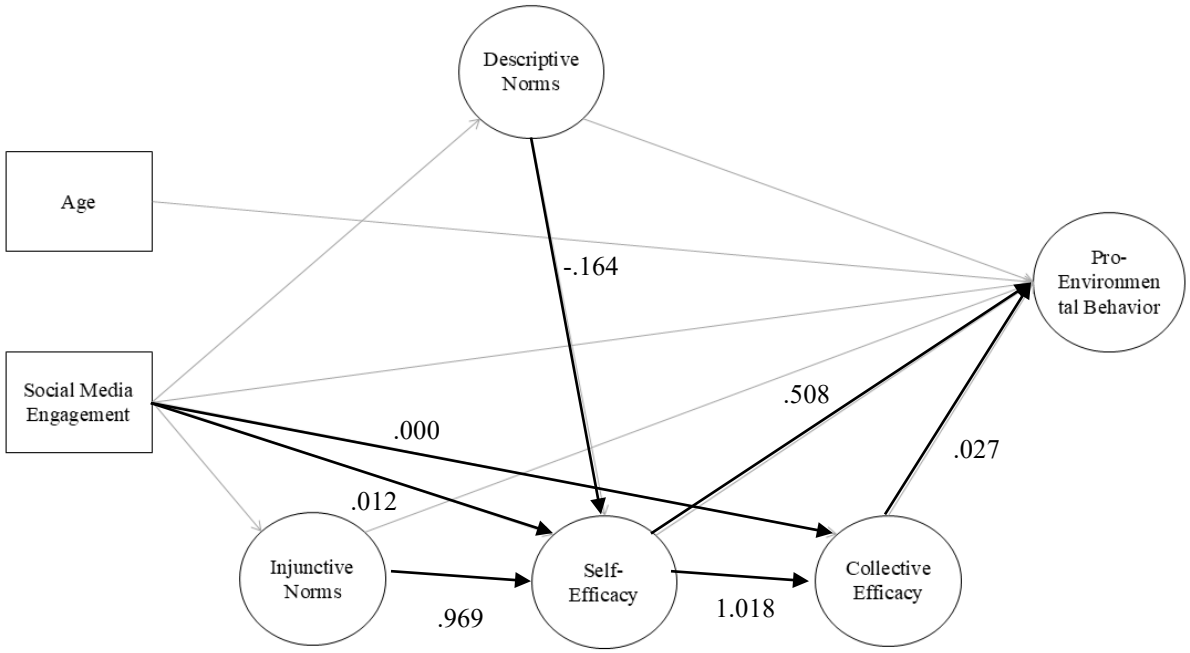
The SEM accounts for 71% of the variability in individual self-efficacy (with age, social media engagement and social norm perceptions; $R^2 = 0.714$, $p<.001$), and 98% of the variation in collective efficacy ($R^2 = .979$, $p<.001$).

Direct Effects, Indirect Effects, and Mediation

Social media engagement's influence on self and collective efficacy also has indirect effects mediated by descriptive and injunctive norms. Figure 17 shows the section of the model dealing with efficacy. Social media engagement's total effect on collective efficacy is .396, with .396 in indirect effects and .000 in direct effects. In this case injunctive and descriptive norms mediate all of social media engagement's influencess on collective efficacy. Social media engagement also shows some indirect effects on self-efficacy in addition to the direct effect of .012. The total effect of engagement on self-efficacy is .398, with .386 in indirect effects. Self-efficacy's influence on PEBs also has indirect effects when mediated by collective efficacy. This indirect effect is small at .034 for a total effect of .661.

Figure 17

Efficacy in the SEM



Note. Coefficients are unstandardized direct effects. All values are significant at the p<.05 level.

Gender

The SEM was analyzed for differences in gender identity, however a lack of statistical significance limits the reliable findings from the analysis. A group analysis was run in Mplus for male, female, and non-binary genders. Table 6 lists unstandardized regression coefficients for the three gender groups. Females show a reduced effect of self-efficacy on PEBs and an increased importance of injunctive norms. Males show an increased effect of social media engagement on PEBs and a negative effect of age on social media engagement, meaning that younger men access Facebook more often than their older cohorts, while the relationship is reversed for female and non-binary participants. Only 28 non-binary respondents self-identified, and this small

sample size caused the SEM's iterative likelihood function to have multiple solutions. The estimates of the non-binary model are included for comparison even though they are unreliable for analysis.

Table 6

Gender Differences in Structural Equation Model Coefficients

	Groups		
Coefficients	**Male**	**Female**	**Non-binary***
Self-Efficacy ON			
Desc. norms	-0.258	0.038	-2.871
Inj. norms	0.785	0.622	3.208
PEBs ON			
Self-efficacy	0.645	0.270	3.305
Coll. Efficacy	-0.558	-0.001	-2.729
Inj. norms	-0.209	0.131	-0.240
Desc. norms	0.387	0.042	0.351
Desc. norms ON			
Social media engagement	0.027	0.027	0.040
Inj. norms ON			
sm engagement	0.027	0.031	0.036
Self-efficacy ON			
sm engagement	0.016	0.014	0.046
Coll. efficacy ON			
sm engagement	-0.003	0.000	-0.002
PEBs ON			
sm engagement	0.016	0.004	-0.012
age	0.006	0.000	-0.002
sm engagement ON			
age	-0.062	0.005	0.160

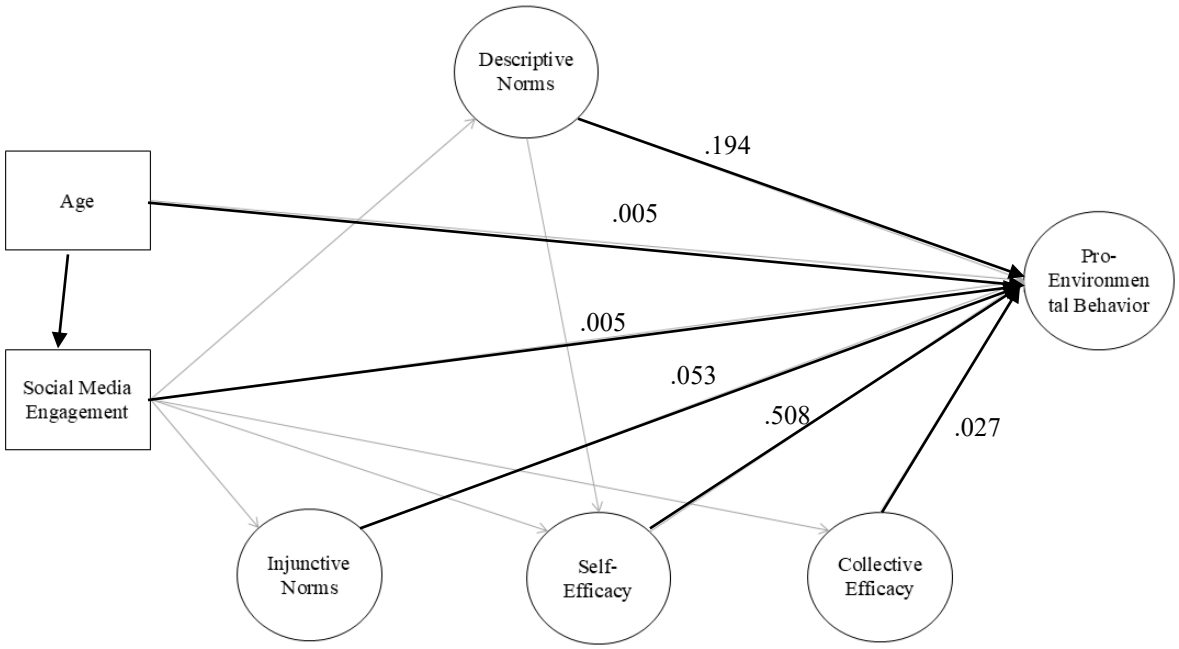
Note. * non-binary results are from a small sample (n=28). Highlighted values are significant at the p<.05 level.

PEB

In the structural model, an individual's PEB is predicted by age, social media engagement, injunctive and descriptive norms, and self- and collective efficacy. An R^2 value of .902 for PEBs indicates that the model accounts for 90% of the variability in PEBs (p=.008). Descriptive norms have a total unstandardized effect of .106 while injunctive norms have a total effect more than five times greater (.572). Age's total effect on PEBs (.007) includes the .005 direct effect shown in Figure 18. Injunctive norms have a much larger (.52) total effect on PEBs than descriptive norms (.106).

Figure 18

PEBs in the SEM

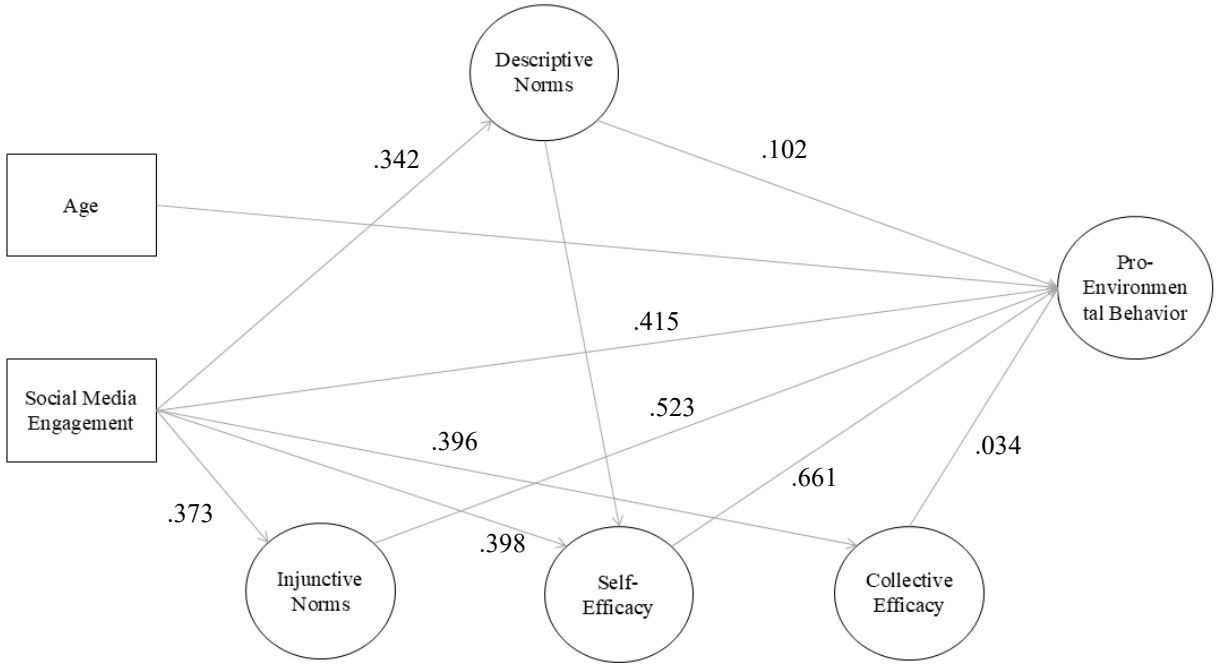


Note. Only unstandardized direct effects on PEBs are shown. All coefficients are statistically significant at the p<.05 level.

Figure 19 shows the standardized total effects of social media engagement on all latent variables, and the total effects of latent variables on PEBs, for the purpose of comparison. Social Media Engagement has a moderate influence on norms, efficacy and PEBs, with a coefficient range of 0.342-0.415

Figure 19

SEM Standardized Total Effects



Research Question #3: What types of learning outcomes result from participation in the Facebook Group, and does the duration of membership impact this learning?

Study participants reported learning outcomes that were attributable to their membership in their native plants-focused Facebook Groups. These participants reported gains in awareness, knowledge, skills, and efficacy. Additionally, responses indicate a progression of learning outcomes over time, with more recent members demonstrating greater awareness and techniques

for removing exotic species, while more long-term members report acquiring more advanced plant identification skills and propagation techniques.

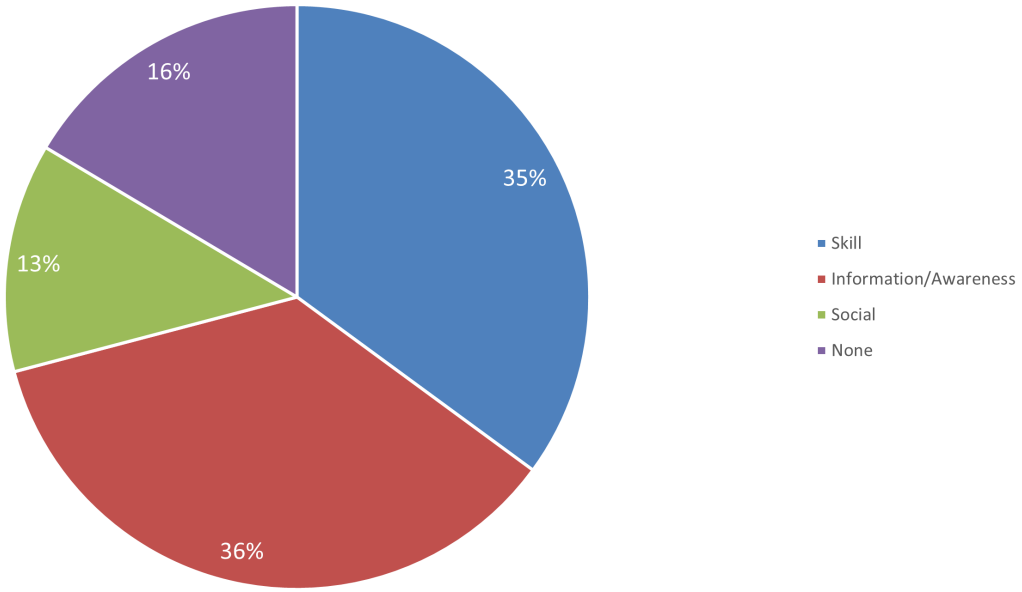
Open-Ended Questions

There were 667 participants who answered the open-ended question asking them what they learned from participating in a native plant-related Facebook Group. Figure 20 shows three categories of response related to TPB constructs. Thirty-five percent of respondents (*n* = 233*)* reported building skills and skill confidence. These skills included plant identification, the maintenance of native plants, and various propagation techniques such as cold stratification and rooting from cuttings. Respondent #165, for example, said they learned "mostly plant identification." Participant #565 reported learning "that many native seeds require something called cold stratification and warm stratification in order to germinate".

Thirty-six percent of participants (*n* = 240) reported learning outcomes related to information and awareness. This category includes reports of learning about new species, nativity of plants, ecological benefits, and plant niche (habitat requirements). Participant #78 wrote "the importance of native plants to all the local pollinators." Respondent #14 reported learning that "[d]ifferent cultivars of the same plant may be invasive and not native (jasmine, wisteria, passionflower, etc) and it is important to ensure you have the correct one." Participant #130 mentioned "[c]ompanion planting, particularly for maintaining bloom production across seasons."

Figure 20

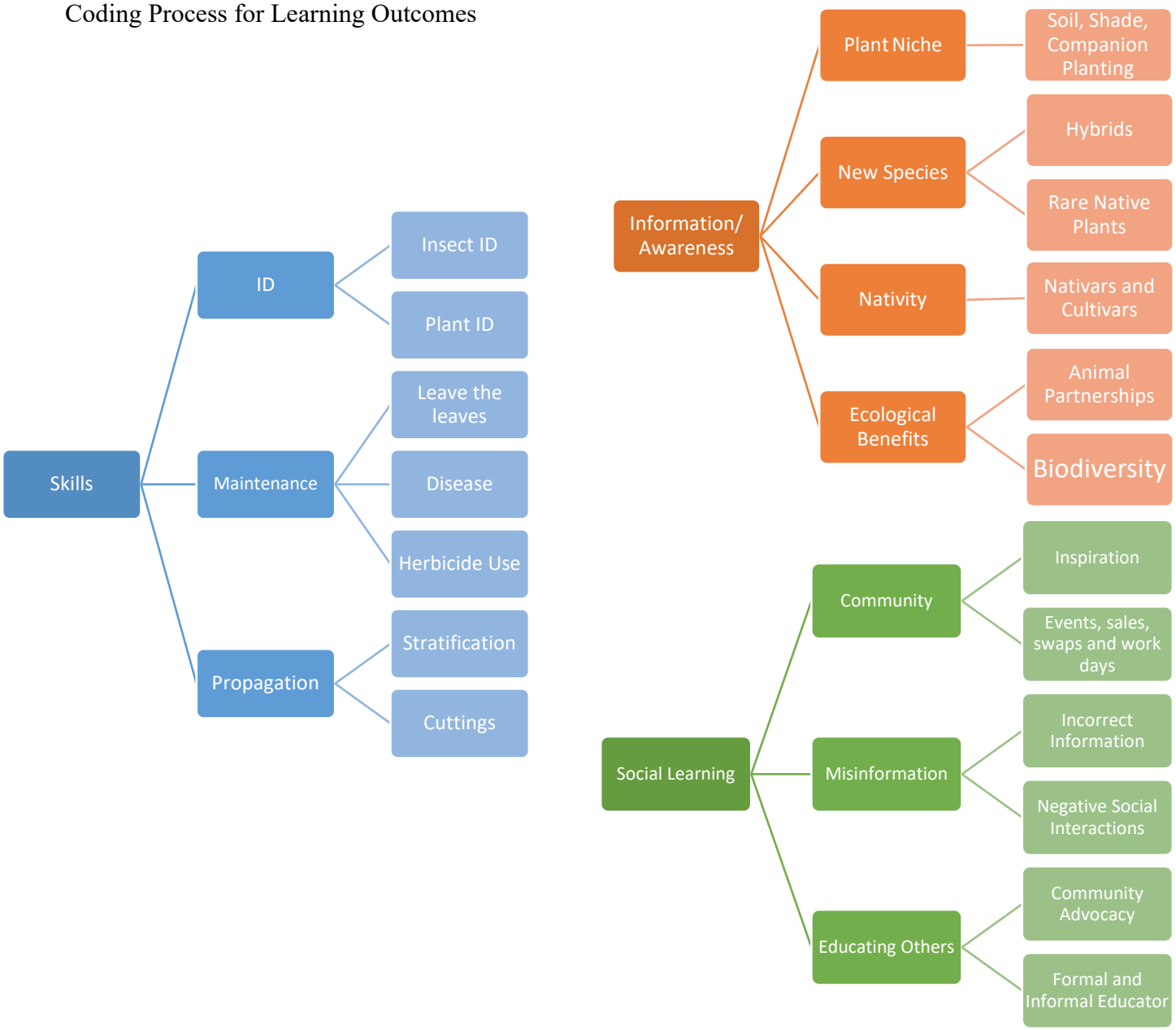
Participants' Perception of Learning Through Facebook Groups



Thirteen percent (n = 87) of respondents reported social learning through the Group, which includes learning about social norms, meet-ups, and getting to know other members. Figure 21 shows how the open inductive coding of the open-ended questions resulted in the larger categories. One respondent, #317, learned that "native plant enthusiasts are really mean spirited when pushing their beliefs regarding native plants," or #329, who learned "about a Group meeting to remove invasives from parkland." Sixteen percent (n = 113) reported that they did not learn from their Facebook Group such as participant #521 who said, "Not much I mostly know more than what's posted," or #340 who wrote that "I've learned more from the actual [native plants] society and magazine than the FB Group". Other participants reported learning about additional resources from other members of the Facebook Group. One typical example of this comes from survey #520 who learned "more places to look things up" or participant #398 who learned "how to properly use BONAP [plant distribution] maps."

Figure 21

Coding Process for Learning Outcomes



Participants also reported the length of time they had been members of their Facebook Group. Table 7 shows the differences in learning between respondents who have been members 0-2 years and members belonging for 3 or more years. There were 267 responses from newer users (0-2 years) and 231 from more experienced users (3+ years). These two-group t-test results

suggest that newer users have different learning foci, including how to remove exotic and invasive species, general awareness of native plants, nativity (whether species, cultivars, or varieties are native), and plant niche (specific requirements such as shade, wetness). More experienced users report learning more ID and propagation skills. There may be factors other than length of membership contributing to these differences, this analysis does not imply causality, only correlation.

Table 7

Effects of Membership Duration on Learning

# of Years	**0-2**	**3+**
Total	267	231
ID	54	[65]
Exotic Replacement	[60]	50
Community	11	13
Awareness	[36]	24
Inspiration	5	5
Nativity	[37]	25
None	31	35
Plant niche	[36]	16
Propagation	18	[30]
Resources	2	8
Suppliers	25	22
Swaps/Sales	5	11

Note. Boxes indicate significantly higher-than-expected means.

Research Question #4: What are the differences in rules, moderation, virality, nature of the online discourse, and the associated impact on promoting PEB in three regional Facebook forums.

Group Characteristics and Rules

The three Facebook Groups sampled in this study were the North Carolina Native Plant Forum (NC in Table 5), the California Native Plant Society (CA), and Native Plants of the Northeast (NE). Each is a public Group, wherein posts and membership is visible to anyone with an internet connection. No Facebook account is necessary. The membership of the NE Group is more than twice the membership of the other Groups and contributed more than twice as many participants as the other Groups, with each Group having a response rate of .003 (CA), .004 (NC), and .004 (NE). Each Group has administrators and moderators who enforce Group rules and approve memberships and posts. Each Group also has members with "expert" badges for knowledgeable members who can confirm identifications. Each Group has a unique set of rules concerning the content and tone of posts. All three of these Groups limit discussions to plants native to their respective geographical ranges before 1492 except in the case of an ID request (where the original poster doesn't know the native/exotic status). All three Groups limit advertising and require that a detailed location or ecoregion is listed with each post. Other rules, such as civility, vary from Group to Group. Two of the Groups prohibit the praise of non-native species and the bashing of native species. The same two Groups (NE and NC) ask members with ID requests to use the search bar before posting to minimize redundant ID requests. Only the NE Group explicitly forbids posts about insects, fungi or edible/medicinal plants. The North Carolina and California Groups are both around 15 years old in 2024 while the Northeast Group is just over five years old. The comparison of the three Groups is detailed in Table 8.

Table 8

Facebook Group Comparison

GROUP	NE	NC	CA
# of Admins/mods	6	21	7
Group experts	9	45	11
Members (11/16/2024)	215,183	97,901	85,954
Participants	777	407	224
Created	2/18/2019	2/26/2009	10/7/2008
Posts in October	329	304	524
RULES			
Native spp only	✓	✓	✓
Include Location	✓	✓	✓
ID here as last resort	✓	✓	✗
No insect/disease posts	✓	✗	✗
No fungi	✓	✗	✗
No Non-native praise	✓	✓	✗
No edible/medicinal	✓	✗	✗
ID include links	✓	✓	✗
No native bashing	✓	✓	✗
No advertising	✓	✓	✓
Civility	✗	✓	✓
Post quality	✗	✓	✗

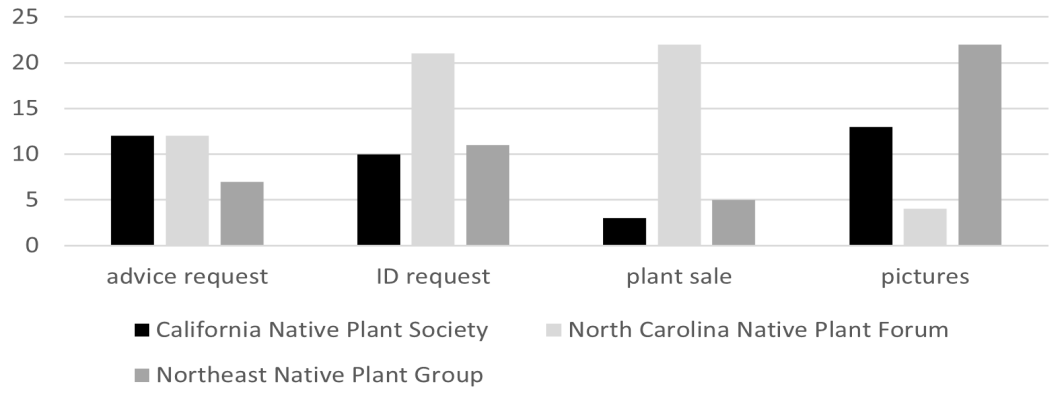
Group Content

Each of the three studied Facebook Groups has its own profile, character, and culture despite many similarities. In this study, 50 consecutive posts were sampled from each of the three sampled Facebook Groups during three days in October, 2024. Of the 150 posts analyzed in this study, 28% of posts (n =42) were ID requests for unknown plants, 26% were pictures of various native plants (n = 39), 21% were non-ID advice requests (n = 31) such as plant recommendations in a certain spot, and 20% were notifications of plant sales or swaps (n = 30). These four categories accounted for 95% of the sampled posts. These categories, however, varied

by Facebook Group. The NCNPF is dominated by ID requests and sale/swap notifications while the CNPS is dominated by plant pictures as seen in Figure 22.

Figure 22

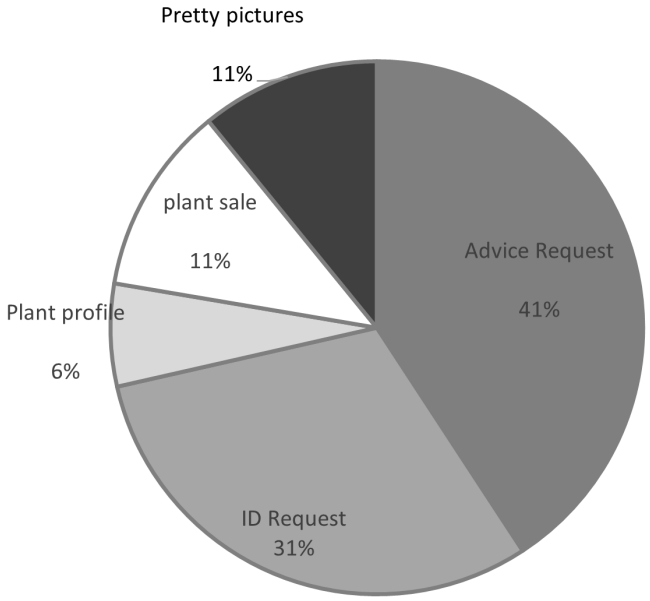
Post Type Comparison Among Three Facebook Groups



Each of these post types has different impacts on users of the Facebook Group. One measure of a post's impact (particularly on norms) is its virality. Virality is defined here as the number of likes, comments, and shares each post receives. Figure 23 shows the virality of the various post types, including plant profiles (detailed information on one plant, including pictures and links), which make up a small number of posts overall but are liked and shared frequently.

Figure 23

Virality By Post Type



ID and advice requests attract nearly ¾ of all comments (n=1,379), 34% of all shares (n=140), and 38% of all likes (n=3,948). Table 9 shows that the most liked category of posts was pictures of plants (n=3,558), and the most shared category at 37% was plant profile (n=153; a picture of a native plant with accompanying detailed information on habitat and care).

Table 9

Virality of Post Types

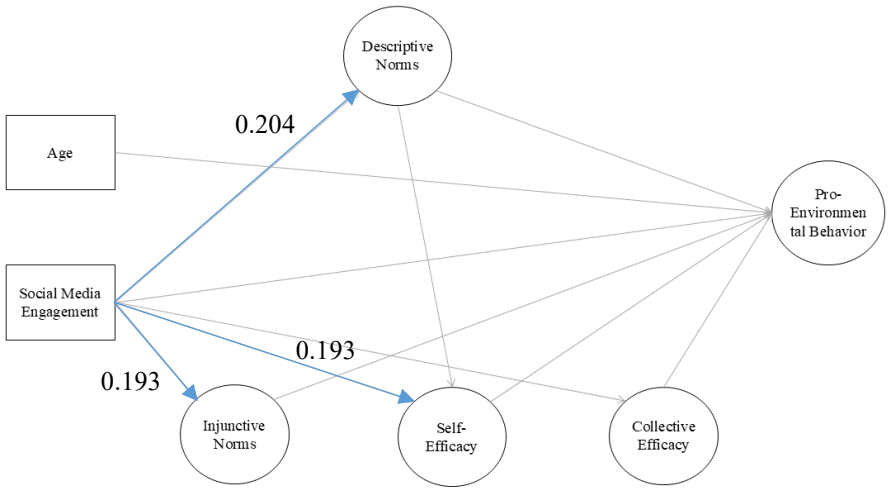
	Likes	Comments	Shares
Advice Request	2192	787	104
ID Request	1756	592	36
Plant Profile	2172	120	153
Plant Sale/Swap	793	221	42
Plant Pictures	3558	210	78

SEM Groups Analysis

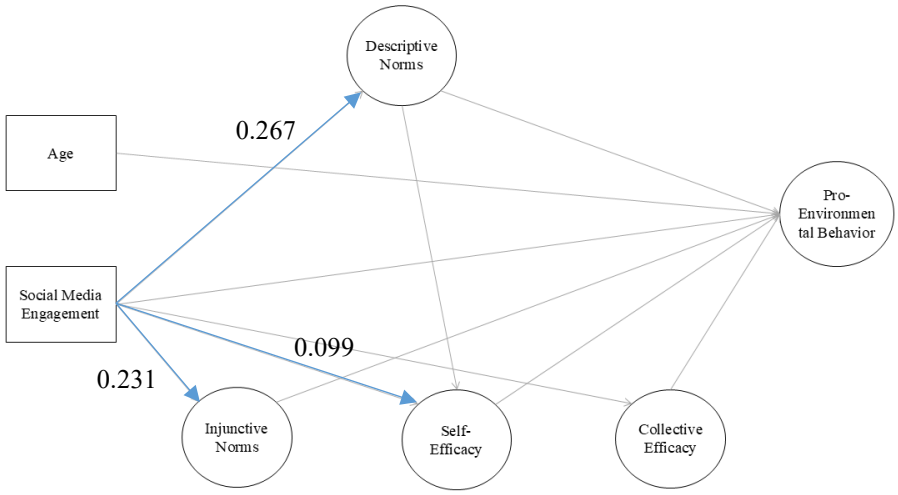
Research question four seeks to understand whether differences in Group administration affect members' PEBs. In order to measure any effect of these Group differences on member PEBs, a groups SEM analysis was run in Mplus to compare the modeled relationships between factors in the three sampled regional native plant-focused Groups. The Mplus groups analysis output is included in Appendix B, and Figure 24 shows the similarity in coefficients relating social media engagement to the four chosen factors. The CNPS shows a smaller effect of engagement on self-efficacy than the other groups, and in the NENPG, engagement has a larger influence on collective efficacy. The CNPS may show less growth in self-efficacy because it is dominated by native plants pictures instead of more skill-building advice requests. The NENPG's higher effect on collective efficacy may be due to regional cultural differences. In two groups (NCNPF and CNPS), social media engagement predicts descriptive norms more significantly, but in the NENPG, it predicts injunctive norms more strongly. The remaining coefficients were not statistically significant at the $p < .05$ level, and so the coefficients are not reliable for analysis.

Figure 24

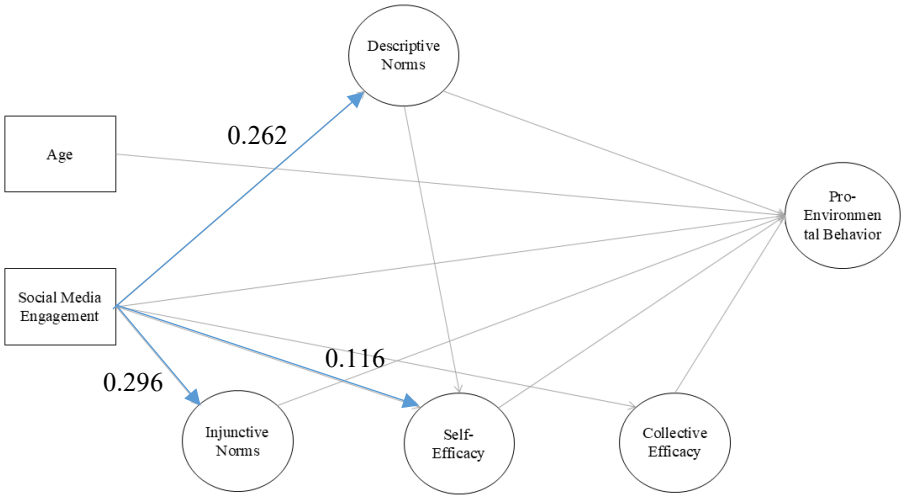
Group Comparison of Standardized SEM Coefficients



NCNPF



CNPF



Note: All coefficients depicted in this figure are significant at the $p < .05$ level.

CHAPTER 5:
DISCUSSION

More than 1,500 members of Facebook Groups focused on native plants responded to the survey in this dissertation study. The resulting data revealed a sample with skewed gender, race, and age characteristics which influence all of the findings. Results showed that members use the Groups to identify plants, view pictures of native species, share advice, and find plant sales and swaps. The SEM analysis revealed the widespread influence of social media engagement on efficacy, norms and PEBs, as mediated primarily by self-efficacy and injunctive norms. The model explained 90% of the variability in PEBs. Various existing studies find that social media engagement leads to descriptive norms and that these norms have the largest impact on PEBs, but this dissertation finds a clear and contradictory pattern. Data in this study demonstrated that self-efficacy and injunctive norms predict PEBs significantly more than either collective efficacy or descriptive norms, which correlates negatively with both PEBs and social media engagement. This chapter examines the results by research question.

Research Question #1: What are individuals' native planting practices/PEBs and how much can be attributed to using one of the subject Facebook Groups?

Regarding pro-environmental behavior, more than 80% of study respondents report recycling and reducing plastic waste daily. They also reported removing exotic invasives from 7,373 acres and planting 6,098 acres with native species due to their membership in a native plants-focused Facebook Group. However, 17% of respondents said their membership did not impact their planting. Reasons varied from yards/renting to getting info elsewhere and being too new to the Group. Almost half of respondents, 47%, said that Group membership led to planting native and pollinator gardens. The remaining respondents (36%) attributed exotics removal or propagation techniques to their Group membership, but not the planting of native species. Prior researchers have found correlations between social media and PEB, but could not attribute the

higher PEB directly or in part to participation in the social media Group (Allison et al., 2023; Robelia et al., 2011). These self-reports indicate that more than three quarters of the sample attribute some PEB to their participation in the native plants Facebook Group. This dissertation represents the first attribution of PEB to social media engagement.

The SEM predicts 90% of the variability in PEBs based on age, social media engagement, norms, and efficacy, indicating that the model is relatively inclusive of the important predictive factors. PEB is most strongly predicted by self-efficacy. A one standard deviation change in self-efficacy predicts a .66 standard deviation change in PEB frequency. This means that a participant's confidence in their ability to plant native plants is crucial to successful PEBs. Self-efficacy is often cited as the best predictor of PEBs (Boulianne & Ohme, 2022; Pradhananga & Davenport, 2022) and this study's results confirm this finding for U.S. social media-based science learning. In the Theory of Planned Behavior's "I can and should" mantra, self-efficacy is the "I can" piece. Once the behavior seems achievable, people are more likely to produce that behavior. Injunctive norms have the second most significant influence on PEBs, where a one standard deviation increase in injunctive norm perception predicts a .523 standard deviation increase in PEBs. Injunctive social norms provide the "I should" part of TPB, reflecting the participant's perception of societal expectations. Social media engagement has a comparably significant predictive capability for PEBs (ʎ=.415). Social media's power to predict PEBs is mediated by (works by using) self-efficacy and injunctive norms. Descriptive norms and collective efficacy influence PEBs less (ʎ=.102, .034, respectively). Descriptive norms and collective efficacy would produce a mantra such as "we can and we do", reflecting a more collectivist idea of behavior.

Previous studies have found that knowledge is not predictive of higher PEBs (Abdullah et al., 2022; Beech, 2020), which may indicate the futility of environmental education (Bolderdijk et al., 2013). Environmental education is not just about knowledge but also skills, attitudes, and behaviors. This and other research shows that learning comprises not only knowledge acquisition, but also these skills, attitudes, and behaviors (efficacy, norms, and PEBs). Efforts to increase PEBs should focus on these other facets of science learning beyond the transmission of facts. The findings of this dissertation indicate that skill-building through social media that results in higher self-efficacy is a strong predictor of PEBs, and that the expression and endorsement (via virality) of injunctive social norms (such as Leave the Leaves or No Mow May) is similarly and strongly predictive of native landscaping behaviors.

Research Question #2: How do key factors (social norms, social media engagement, self-efficacy, collective efficacy, age, and gender) interact to predict individuals' PEB?

Social Media Engagement

The study of human behavior is notoriously complex and structural equation modeling helps to identify the relative effects of multiple factors on behavior. In order to understand how to encourage more native landscaping behaviors, it is important to understand what factors contribute to this behavior.

This study's participants show different social media engagement patterns than Facebook's platform-wide trends. The average respondent to this study's survey logs into their Facebook feed 10.23 times per week (range 0 - 52) versus 8 times per week worldwide (Liedke, 2021). Older participants engage with social media more than younger participants, which is in line with international data on Facebook use (Moretto et al., 2022). Men in this sample show the reverse

trend, however, at only 12% of the respondents, the trend is just at the edge of statistical significance.

This study found that an individual's social media engagement level predicts descriptive and injunctive norm perception, self-efficacy, and ultimately, PEBs. This aligns with recent Chinese research on social media engagement's influence on PEBs (Han et al., 2021; Meng et al., 2023). We also know that this relationship seems to break down for private sphere PEBs, those that are conducted in private and therefore are less susceptible to social norms, such as the study of a UK food retailer trying to reduce food waste at home (Young et al., 2018). In the case of native landscaping, the behavior is public enough to make it susceptible to social norms. These details are partly why studies of PEBs have such different outcomes. PEBs vary in their visibility and therefore, their sensitivity to social norms, social media engagement, and efficacy.

Norms

In order to understand whether or not social media affects an individual's perceptions of social norms, this study asked participants to report their personal Facebook usage and their agreement with statements about social norms. Findings showed that social media engagement and age together explained only 12% of the variability in descriptive norms, and 14% of the variability in injunctive norms. These relatively low numbers reflect the fact that social norms are exogenous variables in the SEM (the factors that combine to form social norms are not explicitly modeled, other than age and social media exposure). These findings show that social media engagement affects injunctive norm perception more than descriptive norm perception. Han and Cheng's (2020) research on Chinese social media users found that descriptive norms were influenced by social media more than injunctive norms, but these effects have not been modeled in a U.S. context, so differences in norms and how they interact with media are

expected in different cultural contexts. The same paper found that descriptive norms have a larger influence on PEBs than injunctive norms, whereas this research finds the opposite pattern (Han & Cheng, 2020b). Social norms are specific to their socio-political and cultural contexts, so it is reasonable to expect differences between countries. Han and Cheng (2020) posit that China's more collectivist culture and centralized society would favor descriptive norms over injunctive. Other researchers found that descriptive norms are most predictive in cultures seeking to manage impressions and maintain control against threats (Gelfand & Harrington, 2015). These differences are important for educators to understand in the international world of social media, where membership and information flow across international boundaries.

Research Question #3: What types of learning outcomes result from participation in the Facebook Group, and does the duration of membership impact this learning?

Study participants identified learning outcomes attributable to their membership in a Facebook Native Plants Group, which included awareness, information/knowledge, skills, efficacy, norms, and social learning about other members.

Learning Outcomes

Eighty-four percent of this study's respondents said they have learned from being a member of their native plants-related Facebook Group. Among the 16% that did not, some explained that they get their information from other sources. Thirty-six percent of the respondents reported learning information and awareness about plants, including whether they are native or exotic, their particular ecological benefits, and the plight of pollinators. Thirty-five percent said they learned specific skills such as seed stratification and plant identification, and 13% reported social learning including inspiration, local suppliers, and additional resources. This learning seems to

progress over time as shown by the differences in reported learning between newer and more senior members. Newer members report learning more about replacing exotics, pollinator awareness, and the specific needs of individual plants, while more senior members report learning ID and propagation skills. This progression makes sense and may explain some complaints about too many IDs and impatient experts. Some report frustration with the Facebook Groups due to differing previous knowledge levels. More experienced users complain that the forums are dominated by the same ID requests over and over, while less knowledgeable users expressed frustration with "mean" experts. These findings suggest that Group members experience a predictable and self-guided progression of learning over time from general awareness of the issue through to very specific skill-building. Additionally, sources of negative social interactions in the Group may have a basis in clashes between newer and more senior members. Practically, this gives administrators insight into these negative social interactions, which do impact members' engagement.

Skill Building and Efficacy as Learning Outcomes

This study's SEM model found that social media engagement predicted self-efficacy and collective efficacy comparably (regression coefficients of .398 and .396 respectively), as described in RQ#2, but the two closely related constructs predict PEBs differently. Self-efficacy is the best modeled predictor of PEBs (.661), while collective efficacy is the worst (.034) among the factors modeled in this research. This means that while social media predicts self- and collective efficacy essentially equally, self-efficacy leads to native landscaping behaviors much more often than collective efficacy. Previous studies hypothesize that collective efficacy increases PEBs by increasing self-efficacy (Jugert et al., 2016) and that collective efficacy predicts action only when tasks are of medium difficulty (Reese & Junge, 2017). A Taiwanese

SEM study finds that collective efficacy is a stronger predictor of PEBs than self-efficacy and hypothesizes that this pattern holds true in collectivist cultures (Chen, 2015). This study's findings are inconsistent with those studies in that it found collective efficacy to be minimally predictive of PEB, while self-efficacy was very highly predictive. Perhaps the collective goals of native landscaping (e.g., stopping the decline of pollinator habitat, saving monarch butterflies) are difficult to pursue in an individualistic culture, such that individual gardeners feel some level of hopelessness around the collective goals, but not around their own yards.

The SEM accounted for 71% of the variability in self-efficacy by accounting for age, social media engagement, and norm perceptions. The SEM predicts 98% of the variability in collective efficacy with the same variables, since the SEM treats collective efficacy as a result of self-efficacy. This theoretical relationship was based on prior research, but this study argues that collective efficacy is influenced by much more than self-efficacy, and predicts PEBs very differently from self-efficacy.

The SEM also showed that efficacy was highly positively correlated to injunctive norms but negatively correlated to descriptive norms. This means that participants with high self-efficacy for native landscaping behaviors agreed strongly with injunctive normative statements but not descriptive normative statements. Participants with high self-efficacy believed that native landscaping was something they "should" do, but believed that others were not landscaping with native plants. This finding disagrees with research from China and Australia that found descriptive norms more predictive of PEBs than injunctive norms (Borg, 2022; W. Han et al., 2021) but agree with research from the U.S. that finds PEBs most strongly linked to self-efficacy and injunctive norms (Pradhananga & Davenport, 2022).

Research Question #4: What are the differences in rules, moderation, virality, nature of the online discourse, and the associated impact on promoting PEB in three regional Facebook forums.

Data collected from 1,521 respondents from three large state-wide or regional native plants FB Groups shows that users of these Groups are older (mean = 53), whiter (89%), and more female (85%) than the Facebook population or the general U.S. population. The 2024 National Gardening Survey (2024) reports that gender and age are fairly evenly distributed amongst gardeners, and Facebook statistics show that only 43% of Facebook users are women ("Social Media and News Fact Sheet," 2024). The reason for the dramatic gender skew in the Facebook Group samples could be a result of differences in interest around native plants or pollinators in general. However, it could also be a result of an algorithm that favors showing this content to women or simple sampling bias. It would be helpful to know the gender composition of the whole population of native plants Facebook Group members, but Facebook policy does not currently allow that particular analysis. As of the writing of this dissertation, these policies are being revised and may be different in the future.

Group Comparison

The three sampled Groups are all public, and survey responses were provided by 0.3-0.4% of the Group members in each Group. Each one has admins and moderators, members with expert badges, and a set of rules for members to follow. Most of these rules, such as limiting discussions to native species are shared between all three Groups, whereas only one of the Groups explicitly prohibits posts on insects. One of the Groups has significantly more Group

experts than the other two, but the large number of ID requests in this Group compared to the others can explain the need for constant moderation.

In posts sampled from each of the three Groups over 2-3 days in October, 28% of the sampled posts were ID requests (n=42), 26% were pictures of native plants (n=39), 21% were non-ID advice requests (n=31), and 20% were notifications of plant sales or swaps (n=30). These four categories accounted for 95% of the sampled posts. The most viral posts were plant pictures, the most shared posts were plant profiles (detailed posts dedicated to one native species), while requests for plant IDs and advice together make up almost three-quarters of all comments.

While the three groups show similar impacts of social media engagement on norms and efficacy, the factors that predict PEB for the three Facebook Groups' members are not significant. These results indicate that while the three groups are administered differently, are in different areas of the US, and have significantly different content, they have similar effects on norms and efficacy. This is a significant finding because it suggests that rules and administrative choices do not effect the norm perceptions or self-efficacy of Group members. This is a finding that has not been recorded in existing literature and should be helpful to educators using Facebook Groups.

Summary

The sampled members of these three native plant-based Facebook Groups engage in recycling behaviors similarly to the average US resident, but engage in native planting practices at a very high rate, with participants reporting thousands of acres treated, creating real increases in local biodiversity. Three quarters of those members attribute these PEBs to their membership in the Facebook Group. These results show that these learning communities have the ability to encourage PEBs on a large scale. The way in which PEBs are encouraged is equally important.

This study finds that self-efficacy, social media engagement, and injunctive norms predict PEB the best, while demographics, descriptive norms, and collective efficacy have little predictive power. This finding is significantly different from previous findings from abroad which show descriptive norms as being the most predictive. This difference can be explained by cultural and media ecosystem differences in different countries, and/or by differences in PEBs.

Most Group members report learning from these Facebook Groups, and characterize their learning as skills, knowledge, social learning, and resources. This triangulates the findings of PEB increases, by showing increases in efficacy, knowledge, and norm perception, as predicted by the conceptual model used for this dissertation.

Finally, this study finds little correlation between administrative Group decisions and PEBs, suggesting that the ability of social media Groups to leverage user-generated content and the social media platform is independent of administrators' choices within the platform.

Limitations

This dissertation's findings and conclusions are limited in their reliability and broader applicability. One reason for the limitations is the sample of participants. The sample (1,521 participants) was demographically distinct from both the wider Facebook population and the larger U.S. population. The sample may be representative of these native plants-focused Facebook Groups, but current Facebook data policies make that difficult to explore. It is also possible that the sample is not fully representative of the population. In this author's previous research on these forums (Harold & Johnson, in review) found a similar gender ratio. It is also important to note that many PEB factors were not modeled in this research study, so it is not an exhaustive exploration of the mediation and effects of social media on PEBs.

Every statistical data analysis method has limitations, and SEMs are no exception. SEMs are limited by the assumptions made by the analyst, by data handling, and by theoretical judgments made in the respecification process. In the case of this study, the SEM cannot imply causality because the research design and sampling method do not measure change over time.

Recommendations

This dissertation study should help informal science and environmental educators utilize social media tools to create communities that believe they can and should engage in PEBs. A combination of self-efficacy, injunctive social norms, and social media engagement predicts high levels of PEBs. These platforms utilize informational, social, and experiential functionalities that traditional media lacks. Traditional media like television and newspapers represent a one-way conversation, while social media harnesses social interaction to enforce norms and increase users' self-efficacy with confidence in skill development. Previous literature shows us that social media is often a more powerful way to encourage PEB than traditional media, and this dissertation shows how.

This dissertation finds that in the US, injunctive norms are powerful correlates with native planting behaviors. These injunctive norms are stated and reinforced through user-generated content and virality measures, including likes and shares. Posts and Group rules supporting these injunctive norms positively affect the desired behaviors. In these native plant groups, one example of this kind of normative post is the popular "Leave the leaves", which states that we should leave tree leaves on our lawns whenever possible to provide pollinator habitat through the winter months. These types of posts help establish and internalize these powerful injunctive norms.

Social media Groups should also focus on developing members' self-efficacy. Repetitious plant ID requests help members develop their ID skills through participation in the ID process, while ensuring that an expert with reliable information can make corrections. In-person meetups with experts and other members, such as swaps, lectures, and workdays, should be encouraged as ways to build skills and confidence offline. Plant identification (and distinctions between cultivars and closely related species) is a skill that is central to native planting behavior and requires time and instruction to develop.

Further studies with experimental or quasi-experimental designs could improve the reliability of the research and confirm causality in the relationships between modeled constructs. Additionally, the role of collective efficacy in encouraging PEB should be further investigated, including how collective efficacy is built and under what circumstances it has a significant effect on PEB.

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APPENDICES

Appendix A: Survey

Q1 You are being asked to participate in a research study about the impacts of social media on landscaping decisions. If you participate in this study, you will participate in the survey and allow the researchers to access the information as data for research. The information that will be used from the survey as research data includes: demographic information and your use of Facebook Groups to learn about native plants. This information will be accessed after August 30, 2024.

This study does not include the collection of your name or other identifying information, you will remain anonymous even to the researchers. This information will only be accessible to the student researcher and faculty advisor and will be kept indefinitely. Participation in this study is strictly voluntary. You can choose not to participate in the study or stop participating at any time by stopping the survey or by contacting me at sharold3@ncsu.edu

There are minimal risks associated with allowing your information to be used as data in this study and there are no direct benefits to you from participating in this research. You will not receive any payment for allowing your information to be used as data for research.

If you have any questions about the research or how it is implemented, please contact the student researcher, Sera Harold, at sharold3@ncsu.edu and 910-685-5705. You can also contact the faculty advisor for this research, Dr. Carla Johnson, at cjohns26@ncsu.edu. If you have questions about your rights as a participant or are concerned with your treatment throughout the

research process, please contact the NC State University IRB Director at IRB-Director@ncsu.edu, 919-515-8754, or fill out a confidential form online at https://research.ncsu.edu/administration/compliance/research-compliance/irb/irb-forms-and-templates/participant-concern-and-complaint-form/

If you consent to participate in this research, please click the "I consent" button

- ○ I consent (1)
- ○ I do not consent (2)

End of Block: Consent Block

Start of Block: Background Information

Q2 How old were you on your most recent birthday?

	18	26	34	43	51	59	67	75	84	92	100
Age in Years ()											

Q3 What is your gender identity?

- ○ Male (1)
- ○ Female (2)
- ○ Non-binary / third gender (3)
- ○ Prefer not to say (4)

Q4 What is your approximate annual household income?

0	5000	10000	15000	20000	25000	30000	35000	40000	45000	50000
	0	0	0	0	0	0	0	0	0	0

Dollars per Year ()

Q5 I describe my race/ethnicity as (check all that apply):

- ☐ Latino/a/x (1)
- ☐ Black/African American (2)
- ☐ White (3)

- [ ] Pacific Islander (4)
- [ ] Asian (5)
- [ ] Native American (6)
- [ ] Middle Eastern (7)
- [ ] African (8)
- [ ] other (9) _____

Q6 I am a member of:

- [ ] The North Carolina Native Plant Forum on Facebook (1)
- [ ] The California Native Plant Society on Facebook (2)
- [ ] Another social media group dedicated to native plants (4)
- [ ] None of These (3)

Display This Question:

If I am a member of: = Another social media group dedicated to native plants

Q7 How long have you been a member of the native plants Facebook Group?

0 1 1 2 2 3 3 4 4 5

Number of Years ()

Display This Question:

If I am a member of: = The North Carolina Native Plant Forum on Facebook

Q8 How long have you been a member of the Facebook Group "North Carolina Native Plant Forum"?

Number of Years

0 1 1 2 2 3 3 4 4 5

Number of Years ()

Display This Question:

If I am a member of: = The California Native Plant Society on Facebook

Q9 How long have you been a member of the Facebook Group "California Native Plant Society"?

	0 1 1 2 2 3 3 4 4 5
Number of Years ()	

End of Block: Background Information

Start of Block: Block 3

Start of Block: Environment

Q10 I engage in green behavior like recycling, reducing energy use, etc.

- ○ Never (1)
- ○ Once a week (2)
- ○ 2-3 times a week (3)
- ○ 4-6 times a week (4)
- ○ Daily (5)

Q11 I would plant more native plants if: (choose all that apply)

- [ ] I had no HOA (1)
- [ ] My neighbors participated (2)
- [ ] I could find a supplier (3)
- [ ] I knew more about native plants (4)
- [ ] They were prettier (5)
- [ ] They required less maintenance (6)
- [ ] It wasn't so difficult to remove the exotics (7)
- [ ] I didn't need a yard where kids could play (8)
- [ ] My property or resale value stayed the same (9)
- [ ] I had no fear of snakes and other wildlife (10)
- [ ] They were cheaper to buy (11)
- [ ] Other (12) _____

End of Block: Environment

Start of Block: The North Carolina Native Plant Forum on Facebook

Display This Question:

If I am a member of: = The North Carolina Native Plant Forum on Facebook

Q12 I visit the North Carolina Native Plant Forum or see it in my Facebook feed _____.

0 5 10 15 20 25 30 35 40 45 50

Number of times per week ()

Display This Question:

If I am a member of: = The California Native Plant Society on Facebook

Q13 I visit the California Native Plant Group or see it in my Facebook feed _____.

0 5 10 15 20 25 30 35 40 45 50

Number of times per week ()

Display This Question:

If I am a member of: = Another social media group dedicated to native plants

Q14 I visit my Native Plant Group or see it in my Facebook feed _____.

0 5 10 15 20 25 30 35 40 45 50

Number of times per week ()

Q15 How many acres of private land do you care for or manage?

0 10 20 30 40 50 60 70 80 90 100

Number of Acres ()

Q16 How many acres of private land have you removed exotic plants from?

0 10 20 30 40 50 60 70 80 90 100

Number of Acres ()

Q17 How many acres of private land have you planted native plants on?

0 10 20 30 40 50 60 70 80 90 100

Number of Acres ()

Q18 I believe that I CAN plant native plants to increase biodiversity.

- Strongly Disagree (1)
- Disagree (2)
- Neutral (6)
- Agree (3)
- Strongly Agree (4)

Q19 I believe that together with a group of native plant enthusiasts, WE CAN plant native plants to increase biodiversity.

- ○ Strongly Disagree (1)
- ○ Disagree (2)
- ○ Neutral (6)
- ○ Agree (3)
- ○ Strongly Agree (4)

Q20 I believe that together with a group of native plant enthusiasts, WE CAN make a difference for pollinators and biodiversity.

- ○ Strongly Disagree (1)
- ○ Disagree (2)
- ○ Neutral (5)
- ○ Agree (3)
- ○ Strongly Agree (4)

Q21 I believe that I CAN make a difference for pollinators and biodiversity.

- ○ Strongly Disagree (1)
- ○ Disagree (2)
- ○ Neutral (5)
- ○ Agree (3)
- ○ Strongly Agree (4)

Q22 I believe that together with a group of native plant enthusiasts, we can make a difference for pollinators and biodiversity.

- ○ Strongly Disagree (1)
- ○ Disagree (2)
- ○ Neutral (5)
- ○ Agree (3)
- ○ Strongly Agree (4)

Q23 Although it may cause inconvenience, I can still change my behavior to help pollinators and mitigate biodiversity loss.

- ○ Strongly Disagree (1)
- ○ Disagree (2)
- ○ Neutral (5)
- ○ Agree (3)
- ○ Strongly Agree (4)

End of Block: The North Carolina Native Plant Forum on Facebook

Start of Block: Block 5

Q24 My friends think that I should plant native plants in my landscaping.

- ○ Disagree Strongly (1)
- ○ Disagree (2)
- ○ Neutral (3)
- ○ Agree (4)
- ○ Agree Strongly (5)

Q25 My friends think that I should avoid pesticide use.

- ○ Disagree Strongly (1)
- ○ Disagree (2)
- ○ Neutral (3)
- ○ Agree (4)
- ○ Agree Strongly (5)

Q26 My friends think that I should replace my grass lawn with native species.

- ○ Disagree Strongly (1)
- ○ Disagree (2)
- ○ Neutral (3)
- ○ Agree (4)
- ○ Agree Strongly (5)

Q27 My friends use native plants in their landscaping.

- ○ Disagree Strongly (1)
- ○ Disagree (2)
- ○ Neutral (3)
- ○ Agree (4)
- ○ Agree Strongly (5)

Q28 My friends avoid pesticide use.

- ○ Disagree Strongly (1)
- ○ Disagree (2)
- ○ Neutral (3)
- ○ Agree (4)
- ○ Agree Strongly (5)

Q29 My friends replace their grass lawns with native species.

- ○ Disagree Strongly (1)

○ Disagree (2)

○ Neutral (3)

○ Agree (4)

○ Agree Strongly (5)

End of Block: Block 5

Start of Block: For the following open-ended questions, please describe your experiences.

Display This Question:

If I am a member of: = The North Carolina Native Plant Forum on Facebook

Or I am a member of: = The California Native Plant Society on Facebook

Or I am a member of: = Another social media group dedicated to native plants

Q30 What is an example of something you learned in the Native Plant Group on Facebook?

_____

_____

_____

_____

_____

Display This Question:

If I am a member of: = The North Carolina Native Plant Forum on Facebook

Or I am a member of: = The California Native Plant Society on Facebook

Or I am a member of: = Another social media group dedicated to native plants

Q31 What is an example of a native plant project that you have finished that was helped by a Native Plant Group on Facebook?

_____

_____

_____

_____

_____

Appendix B:

Mplus Outputs

```
Mplus
VERSI
ON
8.11
MUTHE
N &
MUTHE
N
12/20
/2024       11:10 AM

INPUT INSTRUCTIONS

  Title: CFA Plant Survey 1 - 2nd Order Factor Analysis
  Data: FILE IS "C:\Users\serah\Documents\Research\Dissertation\Qualtrics
  Data\Val1.csv"; Variable: NAMES ARE x1 x4 x5 x2 x6 x3 x10 x11 x12 x7 x8
  x9;
  MISSING ARE .;
  usevariables x1 x5 x6 x3 x7
  x8 x10 x11 x12 MODEL: e1 BY
  x1 x3;


*** WARNING
  Data set contains cases with missing on
  all variables. These cases were not
  included in the analysis.
  Number of cases with missing on all variables:  39
   1 WARNING(S) FOUND IN THE INPUT INSTRUCTIONS



CFA Plant Survey 1 - 2nd Order

Factor Analysis SUMMARY OF

ANALYSIS

Number of groups                                                 1
Number of observations                                         158

Number of dependent variables                                    9
Number of independent variables                                  0
Number of continuous latent variables                            4

Observed

  dependent
X1          X5          X6          X3          X7          X8
X10   variables   X11         X12

  Continuous



Continuous latent variables
   E1          E2          E3          E4
```

Estimator	ML
Information matrix	OBSERVED
Maximum number of iterations	1000
Convergence criterion	0.500D-04
Maximum number of steepest descent iterations	20
Maximum number of iterations for H1	2000
Convergence criterion for H1	0.100D-03

Input data file(s)
  C:\Users\serah\Documents\Research\Dissertation\Qualtrics Data\Val1.csv

Input data format FREE

SUMMARY OF DATA

     Number of missing data patterns   4

COVARIANCE COVERAGE OF DATA

Minimum covariance coverage value   0.100

     PROPORTION OF DATA PRESENT

Covariance Coverage	X1	X5	X6	X3	X7
X1	1.000				
X5	1.000	1.000			
X6	1.000	1.000	1.000		
X3	0.994	0.994	0.994	0.994	
X7	0.968	0.968	0.968	0.962	0.968
X8	0.968	0.968	0.968	0.962	0.968
X10	0.956	0.956	0.956	0.949	0.956
X11	0.968	0.968	0.968	0.962	0.968
X12	0.968	0.968	0.968	0.962	0.968

Covariance Coverage	X8	X10	X11	X12
X8	0.968			
X10	0.956	0.956		
X11	0.968	0.956	0.968	
X12	0.968	0.956	0.968	0.968

UNIVARIATE SAMPLE STATISTICS

     UNIVARIATE HIGHER-ORDER MOMENT DESCRIPTIVE STATISTICS

Variable/ Sample Size	Mean/ Variance	Skewness/ Kurtosis	Minimum/ Maximum	% with Min/Max	Percentiles 20%/60%	Percentiles 40%/80%	Median
X1	3.671	0.472	1.000	2.53%	3.000	3.000	4.000
158.000	0.892	1.897	6.000	8.23%	4.000	4.000	
X5	3.677	-0.936	1.000	1.27%	3.000	4.000	4.000
158.000	0.383	2.870	5.000	4.43%	4.000	4.000	
X6	3.671	-0.814	1.000	1.27%	3.000	4.000	4.000
158.000	0.398	2.545	5.000	5.06%	4.000	4.000	

X3		3.516	-0.468	1.000	1.27%	3.000	3.000
4.000							
	157.000	0.428	1.484	5.000	3.82%	4.000	4.000
X7		3.065	-0.114	1.000	1.31%	2.000	3.000
3.000							
	153.000	0.610	-0.510	5.000	1.31%	3.000	4.000
X8		2.922	-0.060	1.000	7.84%	2.000	3.000
3.000							
	153.000	0.935	-0.278	5.000	4.58%	3.000	4.000
X10		3.232	0.209	1.000	1.32%	3.000	3.000
3.000							
	151.000	0.496	1.205	5.000	4.64%	3.000	4.000
X11		3.471	-0.297	1.000	2.61%	3.000	3.000
3.000							
	153.000	0.837	0.037	5.000	12.42%	4.000	4.000
X12		2.601	0.116	1.000	8.50%	2.000	2.000
3.000							
	153.000	0.697	-0.018	5.000	1.31%	3.000	3.000

THE MODEL ESTIMATION TERMINATED NORMALLY

MODEL FIT INFORMATION

Number of Free Parameters 31

Loglikelihood

H0 Value	-1396.349
H1 Value	-1377.690

Information Criteria

Akaike (AIC)	2854.698
Bayesian (BIC)	2949.638
Sample-Size Adjusted BIC (n* = (n + 2) / 24)	2851.508

Chi-Square Test of Model Fit

Value	37.317
Degrees of Freedom	23
P-Value	0.0301

RMSEA (Root Mean Square Error Of Approximation)

Estimate	0.063	
90 Percent C.I.	0.020	0.098
Probability RMSEA <= .05	0.262	

CFI/TLI

CFI	0.968
TLI	0.949

Chi-Square Test of Model Fit for the Baseline Model

Value	478.067
Degrees of Freedom	36
P-Value	0.0000

SRMR (Standardized Root Mean Square Residual)

	Value
	0.051

MODEL RESULTS

		Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
E1	BY				
X1		1.000	0.000	999.000	999.000
X3		0.973	0.266	3.654	0.000
E2	BY				
X5		1.000	0.000	999.000	999.000
X6		0.886	0.096	9.234	0.000
E3	BY				
X10		1.000	0.000	999.000	999.000
X11		1.537	0.235	6.539	0.000
X12		1.279	0.203	6.295	0.000
E4	BY				
X7		1.000	0.000	999.000	999.000
X8		1.610	0.249	6.474	0.000
E2	ON				
E1		1.637	0.693	2.360	0.018
E3	WITH				
E1		-0.006	0.016	-0.381	0.703
E4	WITH				
E1		-0.012	0.018	-0.642	0.521
E3		0.195	0.044	4.433	0.000
Intercepts					
X1		3.671	0.075	48.865	0.000
X5		3.677	0.049	74.673	0.000
X6		3.671	0.050	73.139	0.000
X3		3.517	0.052	67.428	0.000
X7		3.066	0.063	48.547	0.000
X8		2.922	0.078	37.378	0.000
X10		3.231	0.057	56.576	0.000
X11		3.471	0.074	46.915	0.000
X12		2.602	0.068	38.536	0.000
Variances					
E1		0.116	0.067	1.734	0.083
E3		0.195	0.051	3.820	0.000
E4		0.247	0.064	3.857	0.000
Residual Variances					
X1		0.776	0.098	7.907	0.000
X5		0.032	0.033	0.967	0.333
X6		0.122	0.029	4.195	0.000
X3		0.318	0.054	5.895	0.000
X7		0.363	0.052	7.018	0.000
X8		0.296	0.087	3.402	0.001
X10		0.300	0.042	7.137	0.000
X11		0.378	0.067	5.678	0.000

X12	0.379	0.055	6.847	0.000
E2	0.042	0.119	0.350	0.726

QUALITY OF NUMERICAL RESULTS

Condition Number for the Information Matrix 0.173E-03
(ratio of smallest to largest eigenvalue)

MODEL MODIFICATION INDICES

NOTE: Modification indices for direct effects of observed dependent variables regressed on covariates may not be included. To include these, request MODINDICES (ALL).

Minimum M.I. value for printing the modification index 10.000

	M.I.	E.P.C.	Std E.P.C.	StdYX E.P.C.
WITH Statements				
X10 WITH X7	10.404	0.109	0.109	0.330
X11 WITH X7	13.984	-0.168	-0.168	-0.454

TECHNICAL 4 OUTPUT

ESTIMATES DERIVED FROM THE MODEL

ESTIMATED MEANS FOR THE LATENT VARIABLES

E1	E2	E3	E4
0.000	0.000	0.000	0.000

S.E. FOR ESTIMATED MEANS FOR THE LATENT VARIABLES

E1	E2	E3	E4
0.000	0.000	0.000	0.000

EST./S.E. FOR ESTIMATED MEANS FOR THE LATENT VARIABLES

E1	E2	E3	E4
0.000	0.000	0.000	0.000

TWO-TAILED P-VALUE FOR ESTIMATED MEANS FOR THE LATENT VARIABLES

E1	E2	E3	E4
1.000	1.000	1.000	1.000

ESTIMATED COVARIANCE MATRIX FOR THE LATENT VARIABLES

	E1	E2	E3	E4
E1	0.116			
E2	0.189	0.351		
E3	-0.006	-0.010	0.195	
E4	-0.012	-0.019	0.195	0.247

S.E. FOR ESTIMATED COVARIANCE MATRIX FOR THE LATENT VARIABLES

	E1	E2	E3	E4
E1	0.067			
E2	0.048	0.054		
E3	0.016	0.026	0.051	
E4	0.018	0.029	0.044	0.064

EST./S.E. FOR ESTIMATED COVARIANCE MATRIX FOR THE LATENT VARIABLES

	E1	E2	E3	E4
E1	1.734			
E2	3.903	6.515		
E3	-0.381	-0.395	3.820	
E4	-0.642	-0.662	4.433	3.857

TWO-TAILED P-VALUE FOR ESTIMATED COVARIANCE MATRIX FOR THE LATENT VARIABLES

	E1	E2	E3	E4
E1	0.083			
E2	0.000	0.000		
E3	0.703	0.693	0.000	
E4	0.521	0.508	0.000	0.000

ESTIMATED CORRELATION MATRIX FOR THE LATENT VARIABLES

	E1	E2	E3	E4
E1	1.000			
E2	0.939	1.000		
E3	-0.042	-0.039	1.000	
E4	-0.068	-0.064	0.888	1.000

S.E. FOR ESTIMATED CORRELATION MATRIX FOR THE LATENT VARIABLES

	E1	E2	E3	E4
E1	0.000			
E2	0.179	0.000		
E3	0.107	0.099	0.000	
E4	0.103	0.096	0.066	0.000

EST./S.E. FOR ESTIMATED CORRELATION MATRIX FOR THE LATENT VARIABLES

	E1	E2	E3	E4
E1	999.000			
E2	5.243	999.000		
E3	-0.390	-0.396	999.000	
E4	-0.664	-0.667	13.422	999.000

TWO-TAILED P-VALUE FOR ESTIMATED CORRELATION MATRIX FOR THE LATENT VARIABLES

	E1	E2	E3	E4
E1	0.000			
E2	0.000	0.000		
E3	0.696	0.692	0.000	
E4	0.506	0.505	0.000	0.000

DIAGRAM INFORMATION

  Use View Diagram under the Diagram menu in the Mplus Editor to view the diagram.
  If running Mplus from the Mplus Diagrammer, the diagram opens automatically.

  Diagram output
    c:\users\serah\documents\research\dissertation\qualtrics data\val3a.dgm

      Beginning Time: 11:10:12
         Ending Time: 11:10:12
        Elapsed Time: 00:00:00

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Support: Support@StatModel.com

```
Mplus VERSION 8.11
MUTHEN & MUTHEN
11/23/2024  11:07 AM

INPUT INSTRUCTIONS

  TITLE:

  DATA:
    ! enter the name of the data set
    FILE = "C:\Users\serah\Documents\Research\Dissertation\Qualtrics Data\mplusdata1.csv";

  VARIABLE:
    ! enter the names of the variables in the data set
    NAMES = age engage barriers PEB PEBP x1-x10 income;
      USEVARIABLES = age engage PEB PEBP x1-x10;
  DEFINE:

  MODEL:
    dnorms by x9 x10;
    inorms by x6-x8;
    effs by x1 x3 x5;
    effc by x2 x4;
      PEBG by PEB PEBP;
    engage on age;
    dnorms on engage;
    inorms on engage;
    effs on engage;
    effc on engage;
    PEBG ON effs effc inorms dnorms;
    effc on effs;
      PEBG on engage;
      PEBG on age;
      inorms WITH dnorms;
      effs on dnorms inorms;

  OUTPUT:
  STANDARDIZED;
  MOD;



INPUT READING TERMINATED NORMALLY




SUMMARY OF ANALYSIS

Number of groups                                                 1
Number of observations                                         760

Number of dependent variables                                   13
Number of independent variables                                  1
Number of continuous latent variables                            5

Observed dependent variables

  Continuous
   ENGAGE      PEB         PEBP        X1          X2          X3
```

X4 X5 X6 X7 X8 X9
X10

Observed independent variables
AGE

Continuous latent variables
DNORMS INORMS EFFS EFFC PEBG

Estimator	ML
Information matrix	OBSERVED
Maximum number of iterations	1000
Convergence criterion	0.500D-04
Maximum number of steepest descent iterations	20

Input data file(s)
C:\Users\serah\Documents\Research\Dissertation\Qualtrics Data\mplusdata1.csv

Input data format FREE

UNIVARIATE SAMPLE STATISTICS

UNIVARIATE HIGHER-ORDER MOMENT DESCRIPTIVE STATISTICS

Variable/ Sample Size	Mean/ Variance	Skewness/ Kurtosis	Minimum/ Maximum	% with Min/Max	20%/60%	Percentiles 40%/80%	Median
ENGAGE	10.653	1.698	0.000	16.84%	2.000	6.000	7.000
760.000	119.703	3.087	50.000	2.63%	10.000	16.000	
PEB	4.203	-1.873	0.000	8.82%	3.000	5.000	5.000
760.000	2.377	2.178	5.000	73.03%	5.000	5.000	
PEBP	0.876	17.987	0.000	39.61%	0.000	0.020	0.430
760.000	18.192	390.166	100.000	0.13%	0.500	1.000	
X1	3.257	-1.435	0.000	13.82%	3.000	4.000	4.000
760.000	2.114	0.901	6.000	1.84%	4.000	4.000	
X2	3.212	-1.582	0.000	13.95%	3.000	4.000	4.000
760.000	1.996	0.950	5.000	1.32%	4.000	4.000	
X3	3.189	-1.534	0.000	14.08%	3.000	4.000	4.000
760.000	2.006	0.853	5.000	1.71%	4.000	4.000	
X4	3.225	-1.625	0.000	13.82%	3.000	4.000	4.000
760.000	1.956	1.101	5.000	1.18%	4.000	4.000	
X5	3.212	-1.516	0.000	13.95%	3.000	4.000	4.000
760.000	2.006	0.925	5.000	3.42%	4.000	4.000	
X6	2.939	-0.943	0.000	15.13%	3.000	3.000	3.000
760.000	2.046	0.211	5.000	9.74%	3.000	4.000	
X7	3.089	-0.904	0.000	15.00%	2.000	3.000	3.000
760.000	2.350	-0.078	5.000	15.39%	4.000	4.000	
X8	2.568	-0.552	0.000	15.66%	2.000	3.000	3.000
760.000	1.908	-0.307	5.000	6.18%	3.000	4.000	

X9		2.743	-0.671	0.000	14.87%	2.000	3.000
3.000							
	760.000	2.054	-0.416	5.000	5.92%	3.000	4.000
X10		2.822	-0.667	0.000	15.00%	2.000	3.000
3.000							
	760.000	2.199	-0.430	5.000	9.21%	3.000	4.000
AGE		38.913	-0.490	0.000	26.18%	0.000	39.000
45.000							
	760.000	663.748	-1.164	81.000	0.13%	51.000	63.000

THE MODEL ESTIMATION TERMINATED NORMALLY

MODEL FIT INFORMATION

Number of Free Parameters 53

Loglikelihood

H0 Value	-13509.159
H1 Value	-13350.456

Information Criteria

Akaike (AIC)	27124.319
Bayesian (BIC)	27369.884
Sample-Size Adjusted BIC (n* = (n + 2) / 24)	27201.587

Chi-Square Test of Model Fit

Value	317.408
Degrees of Freedom	64
P-Value	0.0000

RMSEA (Root Mean Square Error Of Approximation)

Estimate	0.072	
90 Percent C.I.	0.064	0.080
Probability RMSEA <= .05	0.000	

CFI/TLI

CFI	0.981
TLI	0.973

Chi-Square Test of Model Fit for the Baseline Model

Value	13329.883
Degrees of Freedom	91
P-Value	0.0000

SRMR (Standardized Root Mean Square Residual)

Value	0.062

MODEL RESULTS

Two-Tailed

	Estimate	S.E.	Est./S.E.	P-Value
DNORMS BY				
X9	1.000	0.000	999.000	999.000
X10	1.053	0.023	45.256	0.000
INORMS BY				
X6	1.000	0.000	999.000	999.000
X7	1.085	0.022	48.847	0.000
X8	0.923	0.022	41.579	0.000
EFFS BY				
X1	1.000	0.000	999.000	999.000
X3	1.022	0.018	57.850	0.000
X5	0.998	0.019	52.276	0.000
EFFC BY				
X2	1.000	0.000	999.000	999.000
X4	0.999	0.009	115.078	0.000
PEBG BY				
PEB	1.000	0.000	999.000	999.000
PEBP	0.384	0.146	2.628	0.009
EFFS ON				
DNORMS	-0.164	0.135	-1.220	0.222
INORMS	0.969	0.137	7.095	0.000
EFFC ON				
EFFS	1.018	0.018	55.688	0.000
PEBG ON				
EFFS	0.508	0.378	1.345	0.179
EFFC	0.027	0.351	0.077	0.939
INORMS	0.053	0.202	0.263	0.792
DNORMS	0.194	0.181	1.073	0.283
DNORMS ON				
ENGAGE	0.041	0.004	9.535	0.000
INORMS ON				
ENGAGE	0.045	0.004	10.625	0.000
EFFS ON				
ENGAGE	0.012	0.003	3.996	0.000
EFFC ON				
ENGAGE	0.000	0.001	0.232	0.817
PEBG ON				
ENGAGE	0.005	0.004	1.176	0.240
AGE	0.005	0.002	3.211	0.001
ENGAGE ON				
AGE	0.035	0.015	2.269	0.023
INORMS WITH				
DNORMS	1.460	0.084	17.447	0.000
Intercepts				
ENGAGE	9.297	0.716	12.976	0.000
PEB	3.556	0.095	37.571	0.000
PEBP	0.628	0.183	3.431	0.001

X1	2.734	0.067	41.093	0.000
X2	2.677	0.066	40.854	0.000
X3	2.656	0.066	40.410	0.000
X4	2.691	0.065	41.374	0.000
X5	2.690	0.065	41.220	0.000
X6	2.457	0.067	36.903	0.000
X7	2.566	0.072	35.866	0.000
X8	2.123	0.063	33.472	0.000
X9	2.304	0.068	34.137	0.000
X10	2.360	0.070	33.620	0.000
Residual Variances				
ENGAGE	118.898	6.099	19.494	0.000
PEB	1.122	0.456	2.460	0.014
PEBP	18.007	0.926	19.443	0.000
X1	0.298	0.017	17.412	0.000
X2	0.070	0.005	12.868	0.000
X3	0.110	0.008	13.734	0.000
X4	0.035	0.004	7.830	0.000
X5	0.197	0.012	16.505	0.000
X6	0.277	0.020	13.700	0.000
X7	0.268	0.021	12.999	0.000
X8	0.400	0.025	16.216	0.000
X9	0.313	0.024	13.219	0.000
X10	0.270	0.024	11.380	0.000
DNORMS	1.537	0.094	16.364	0.000
INORMS	1.524	0.091	16.758	0.000
EFFS	0.520	0.036	14.254	0.000
EFFC	0.041	0.007	6.177	0.000
PEBG	0.117	0.453	0.259	0.795

QUALITY OF NUMERICAL RESULTS

Condition Number for the Information Matrix 0.153E-05
(ratio of smallest to largest eigenvalue)

STANDARDIZED MODEL RESULTS

STDYX Standardization

	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
DNORMS BY				
X9	0.921	0.007	127.880	0.000
X10	0.936	0.006	144.746	0.000
INORMS BY				
X6	0.930	0.006	150.296	0.000
X7	0.941	0.005	174.254	0.000
X8	0.889	0.009	103.385	0.000
EFFS BY				
X1	0.927	0.005	169.044	0.000
X3	0.972	0.002	395.717	0.000
X5	0.950	0.004	241.936	0.000
EFFC BY				
X2	0.982	0.002	595.943	0.000
X4	0.991	0.001	801.196	0.000

PEBG BY				
PEB	0.718	0.137	5.239	0.000
PEBP	0.098	0.040	2.484	0.013
EFFS ON				
DNORMS	-0.161	0.132	-1.221	0.222
INORMS	0.957	0.131	7.297	0.000
EFFC ON				
EFFS	0.988	0.005	219.287	0.000
PEBG ON				
EFFS	0.627	0.481	1.303	0.193
EFFC	0.034	0.446	0.077	0.939
INORMS	0.065	0.246	0.263	0.792
DNORMS	0.234	0.224	1.045	0.296
DNORMS ON				
ENGAGE	0.342	0.033	10.220	0.000
INORMS ON				
ENGAGE	0.373	0.032	11.553	0.000
EFFS ON				
ENGAGE	0.097	0.024	3.991	0.000
EFFC ON				
ENGAGE	0.002	0.010	0.231	0.817
PEBG ON				
ENGAGE	0.048	0.042	1.137	0.255
AGE	0.124	0.045	2.767	0.006
ENGAGE ON				
AGE	0.082	0.036	2.277	0.023
INORMS WITH				
DNORMS	0.954	0.007	133.018	0.000
Intercepts				
ENGAGE	0.850	0.071	11.971	0.000
PEB	2.337	0.094	24.965	0.000
PEBP	0.147	0.043	3.399	0.001
X1	1.880	0.077	24.365	0.000
X2	1.895	0.078	24.230	0.000
X3	1.875	0.078	24.112	0.000
X4	1.924	0.079	24.368	0.000
X5	1.899	0.078	24.371	0.000
X6	1.717	0.074	23.268	0.000
X7	1.674	0.073	22.905	0.000
X8	1.537	0.069	22.128	0.000
X9	1.608	0.071	22.542	0.000
X10	1.592	0.071	22.332	0.000
Residual Variances				
ENGAGE	0.993	0.006	168.043	0.000
PEB	0.485	0.197	2.462	0.014
PEBP	0.990	0.008	126.911	0.000
X1	0.141	0.010	13.884	0.000
X2	0.035	0.003	10.856	0.000
X3	0.055	0.005	11.436	0.000
X4	0.018	0.002	7.284	0.000

X5	0.098	0.007	13.146	0.000
X6	0.135	0.012	11.746	0.000
X7	0.114	0.010	11.216	0.000
X8	0.209	0.015	13.695	0.000
X9	0.153	0.013	11.507	0.000
X10	0.123	0.012	10.150	0.000
DNORMS	0.883	0.023	38.606	0.000
INORMS	0.861	0.024	35.832	0.000
EFFS	0.286	0.021	13.904	0.000
EFFC	0.021	0.004	5.917	0.000
PEBG	0.098	0.342	0.287	0.774

STDY Standardization

	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
DNORMS BY				
X9	0.921	0.007	127.880	0.000
X10	0.936	0.006	144.746	0.000
INORMS BY				
X6	0.930	0.006	150.296	0.000
X7	0.941	0.005	174.254	0.000
X8	0.889	0.009	103.385	0.000
EFFS BY				
X1	0.927	0.005	169.044	0.000
X3	0.972	0.002	395.717	0.000
X5	0.950	0.004	241.936	0.000
EFFC BY				
X2	0.982	0.002	595.943	0.000
X4	0.991	0.001	801.196	0.000
PEBG BY				
PEB	0.718	0.137	5.239	0.000
PEBP	0.098	0.040	2.484	0.013
EFFS ON				
DNORMS	-0.161	0.132	-1.221	0.222
INORMS	0.957	0.131	7.297	0.000
EFFC ON				
EFFS	0.988	0.005	219.287	0.000
PEBG ON				
EFFS	0.627	0.481	1.303	0.193
EFFC	0.034	0.446	0.077	0.939
INORMS	0.065	0.246	0.263	0.792
DNORMS	0.234	0.224	1.045	0.296
DNORMS ON				
ENGAGE	0.342	0.033	10.220	0.000
INORMS ON				
ENGAGE	0.373	0.032	11.553	0.000
EFFS ON				
ENGAGE	0.097	0.024	3.991	0.000
EFFC ON				

ENGAGE	0.002	0.010	0.231	0.817
PEBG ON				
ENGAGE	0.048	0.042	1.137	0.255
AGE	0.005	0.002	2.774	0.006
ENGAGE ON				
AGE	0.003	0.001	2.280	0.023
INORMS WITH				
DNORMS	0.954	0.007	133.018	0.000
Intercepts				
ENGAGE	0.850	0.071	11.971	0.000
PEB	2.337	0.094	24.965	0.000
PEBP	0.147	0.043	3.399	0.001
X1	1.880	0.077	24.365	0.000
X2	1.895	0.078	24.230	0.000
X3	1.875	0.078	24.112	0.000
X4	1.924	0.079	24.368	0.000
X5	1.899	0.078	24.371	0.000
X6	1.717	0.074	23.268	0.000
X7	1.674	0.073	22.905	0.000
X8	1.537	0.069	22.128	0.000
X9	1.608	0.071	22.542	0.000
X10	1.592	0.071	22.332	0.000
Residual Variances				
ENGAGE	0.993	0.006	168.043	0.000
PEB	0.485	0.197	2.462	0.014
PEBP	0.990	0.008	126.911	0.000
X1	0.141	0.010	13.884	0.000
X2	0.035	0.003	10.856	0.000
X3	0.055	0.005	11.436	0.000
X4	0.018	0.002	7.284	0.000
X5	0.098	0.007	13.146	0.000
X6	0.135	0.012	11.746	0.000
X7	0.114	0.010	11.216	0.000
X8	0.209	0.015	13.695	0.000
X9	0.153	0.013	11.507	0.000
X10	0.123	0.012	10.150	0.000
DNORMS	0.883	0.023	38.606	0.000
INORMS	0.861	0.024	35.832	0.000
EFFS	0.286	0.021	13.904	0.000
EFFC	0.021	0.004	5.917	0.000
PEBG	0.098	0.342	0.287	0.774

STD Standardization

	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
DNORMS BY				
X9	1.319	0.040	32.974	0.000
X10	1.389	0.041	33.953	0.000
INORMS BY				
X6	1.330	0.039	33.709	0.000
X7	1.443	0.042	34.485	0.000
X8	1.228	0.039	31.204	0.000
EFFS BY				

X1	1.348	0.040	33.738	0.000
X3	1.377	0.037	36.856	0.000
X5	1.345	0.038	35.268	0.000
EFFC BY				
X2	1.388	0.037	37.610	0.000
X4	1.386	0.036	38.265	0.000
PEBG BY				
PEB	1.093	0.212	5.155	0.000
PEBP	0.420	0.170	2.471	0.013
EFFS ON				
DNORMS	-0.161	0.132	-1.221	0.222
INORMS	0.957	0.131	7.297	0.000
EFFC ON				
EFFS	0.988	0.005	219.287	0.000
PEBG ON				
EFFS	0.627	0.481	1.303	0.193
EFFC	0.034	0.446	0.077	0.939
INORMS	0.065	0.246	0.263	0.792
DNORMS	0.234	0.224	1.045	0.296
DNORMS ON				
ENGAGE	0.031	0.003	10.500	0.000
INORMS ON				
ENGAGE	0.034	0.003	11.938	0.000
EFFS ON				
ENGAGE	0.009	0.002	4.005	0.000
EFFC ON				
ENGAGE	0.000	0.001	0.232	0.817
PEBG ON				
ENGAGE	0.004	0.004	1.138	0.255
AGE	0.005	0.002	2.774	0.006
ENGAGE ON				
AGE	0.035	0.015	2.269	0.023
INORMS WITH				
DNORMS	0.954	0.007	133.018	0.000
Intercepts				
ENGAGE	9.297	0.716	12.976	0.000
PEB	3.556	0.095	37.571	0.000
PEBP	0.628	0.183	3.431	0.001
X1	2.734	0.067	41.093	0.000
X2	2.677	0.066	40.854	0.000
X3	2.656	0.066	40.410	0.000
X4	2.691	0.065	41.374	0.000
X5	2.690	0.065	41.220	0.000
X6	2.457	0.067	36.903	0.000
X7	2.566	0.072	35.866	0.000
X8	2.123	0.063	33.472	0.000
X9	2.304	0.068	34.137	0.000
X10	2.360	0.070	33.620	0.000
Residual Variances				

ENGAGE	118.898	6.099	19.494	0.000
PEB	1.122	0.456	2.460	0.014
PEBP	18.007	0.926	19.443	0.000
X1	0.298	0.017	17.412	0.000
X2	0.070	0.005	12.868	0.000
X3	0.110	0.008	13.734	0.000
X4	0.035	0.004	7.830	0.000
X5	0.197	0.012	16.505	0.000
X6	0.277	0.020	13.700	0.000
X7	0.268	0.021	12.999	0.000
X8	0.400	0.025	16.216	0.000
X9	0.313	0.024	13.219	0.000
X10	0.270	0.024	11.380	0.000
DNORMS	0.883	0.023	38.606	0.000
INORMS	0.861	0.024	35.832	0.000
EFFS	0.286	0.021	13.904	0.000
EFFC	0.021	0.004	5.917	0.000
PEBG	0.098	0.342	0.287	0.774

R-SQUARE

Observed Variable	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
ENGAGE	0.007	0.006	1.138	0.255
PEB	0.515	0.197	2.619	0.009
PEBP	0.010	0.008	1.242	0.214
X1	0.859	0.010	84.522	0.000
X2	0.965	0.003	297.972	0.000
X3	0.945	0.005	197.858	0.000
X4	0.982	0.002	400.598	0.000
X5	0.902	0.007	120.968	0.000
X6	0.865	0.012	75.148	0.000
X7	0.886	0.010	87.127	0.000
X8	0.791	0.015	51.693	0.000
X9	0.847	0.013	63.940	0.000
X10	0.877	0.012	72.373	0.000

Latent Variable	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
DNORMS	0.117	0.023	5.110	0.000
INORMS	0.139	0.024	5.777	0.000
EFFS	0.714	0.021	34.685	0.000
EFFC	0.979	0.004	272.001	0.000
PEBG	0.902	0.342	2.636	0.008

MODEL MODIFICATION INDICES

NOTE: Modification indices for direct effects of observed dependent variables regressed on covariates may not be included. To include these, request MODINDICES (ALL).

Minimum M.I. value for printing the modification index 10.000

	M.I.	E.P.C.	Std E.P.C.	StdYX E.P.C.
BY Statements				
DNORMS BY X6	29.468	-0.624	-0.824	-0.576
DNORMS BY X7	34.528	0.722	0.952	0.621

EFFS	BY X8	14.271	-0.146	-0.197	-0.143
EFFC	BY X1	14.692	-0.828	-1.149	-0.790
EFFC	BY X3	14.046	0.848	1.176	0.831
EFFC	BY X8	13.559	-0.133	-0.185	-0.134
PEBG	BY X8	19.673	-0.289	-0.316	-0.229

ON/BY Statements

ENGAGE	ON DNORMS /				
DNORMS	BY ENGAGE	32.186	-22.697	-29.944	-2.737
ENGAGE	ON INORMS /				
INORMS	BY ENGAGE	31.799	-22.505	-29.939	-2.736
ENGAGE	ON EFFS /				
EFFS	BY ENGAGE	48.491	-27.414	-36.944	-3.377
ENGAGE	ON EFFC /				
EFFC	BY ENGAGE	47.043	-26.103	-36.224	-3.311
ENGAGE	ON PEBG /				
PEBG	BY ENGAGE	47.123	-36.326	-39.692	-3.628
EFFS	ON PEBG /				
PEBG	BY EFFS	21.055	0.960	0.779	0.779

ON Statements

EFFS	ON AGE	20.884	0.005	0.004	0.096

WITH Statements

X5	WITH X3	11.906	-0.030	-0.030	-0.205
X7	WITH X3	12.706	0.031	0.031	0.179
X7	WITH X6	12.849	-0.070	-0.070	-0.256
X8	WITH X6	57.235	0.128	0.128	0.386
X8	WITH X7	14.518	-0.069	-0.069	-0.210
X9	WITH X6	21.301	0.073	0.073	0.247
X9	WITH X7	35.684	-0.098	-0.098	-0.339
X10	WITH X5	10.169	0.036	0.036	0.154
X10	WITH X6	85.720	-0.146	-0.146	-0.534
X10	WITH X7	125.077	0.184	0.184	0.685
ENGAGE	WITH EFFS	20.889	-17.173	-23.821	-2.185
AGE	WITH EFFS	20.885	3.339	4.632	0.180

DIAGRAM INFORMATION

Use View Diagram under the Diagram menu in the Mplus Editor to view the diagram.
If running Mplus from the Mplus Diagrammer, the diagram opens automatically.

Diagram output
c:\users\serah\documents\research\dissertation\mplus data\peb2c.dgm

Beginning Time: 11:07:19
Ending Time: 11:07:19
Elapsed Time: 00:00:00

Mplus VERSION 8.11
MUTHEN & MUTHEN
11/30/2024 12:27 PM

INPUT INSTRUCTIONS

TITLE:

DATA:
! enter the name of the data set

```
C:\Users\serah\Documents\Research\Dissertation\Mplus Data\peb2cgroups.out
    FILE = "C:\Users\serah\Documents\Research\Dissertation\Qualtrics Data\groups.csv";

  VARIABLE:
    ! enter the names of the variables in the data set
    NAMES = age engage barriers PEB PEBP x1-x10 gender;
      USEVARIABLES = age engage PEB PEBP x1-x10 gender;
      GROUPING IS gender (1=male 2=female);
  DEFINE:

  MODEL:

      dnorms by x9 x10;
    inorms by x6-x8;
    effs by x1 x3 x5;
    effc by x2 x4;
      PEBG by PEB PEBP;
    engage on age;
    dnorms on engage;
    inorms on engage;
    effs on engage;
    effc on engage;
    PEBG ON effs effc inorms dnorms;
    effc on effs;
      PEBG on engage;
      PEBG on age;
      inorms WITH dnorms;
      effs on dnorms inorms;
     !Model Indirect: PEBG IND inorms;
     !PEBG IND dnorms;


  OUTPUT:
  STANDARDIZED;
  MOD;



*** WARNING
  Data set contains unknown or missing values for GROUPING,
  PATTERN, COHORT, CLUSTER and/or STRATIFICATION variables.
  Number of cases with unknown or missing values:  141
   1 WARNING(S) FOUND IN THE INPUT INSTRUCTIONS



SUMMARY OF ANALYSIS

Number of groups                                                 2
Number of observations
   Group MALE                                                  185
   Group FEMALE                                               1194
   Total sample size                                          1379
```

Number of dependent variables 13
Number of independent variables 1
Number of continuous latent variables 5

Observed dependent variables

Continuous
ENGAGE PEB PEBP X1 X2 X3
X4 X5 X6 X7 X8 X9
X10

Observed independent variables
AGE

Continuous latent variables
DNORMS INORMS EFFS EFFC PEBG

Variables with special functions

Grouping variable GENDER

Estimator ML
Information matrix OBSERVED
Maximum number of iterations 1000
Convergence criterion 0.500D-04
Maximum number of steepest descent iterations 20

Input data file(s)
C:\Users\serah\Documents\Research\Dissertation\Qualtrics Data\groups.csv

Input data format FREE

UNIVARIATE SAMPLE STATISTICS

UNIVARIATE HIGHER-ORDER MOMENT DESCRIPTIVE STATISTICS FOR MALE

Variable/ Sample Size	Mean/ Variance	Skewness/ Kurtosis	Minimum/ Maximum	% with Min/Max	Percentiles 20%/60%	40%/80%	Median
ENGAGE	11.865	1.593	0.000	11.35%	3.000	7.000	10.000
185.000	128.474	2.471	50.000	2.16%	10.000	18.000	
PEB	4.411	-1.877	0.000	1.62%	3.000	5.000	5.000
185.000	1.334	2.693	5.000	76.22%	5.000	5.000	
PEBP	1.036	6.733	0.000	38.38%	0.000	0.040	0.500
185.000	10.758	49.072	30.000	0.54%	0.570	1.000	
X1	3.438	-1.511	0.000	8.11%	3.000	4.000	4.000
185.000	1.673	2.117	6.000	3.24%	4.000	4.000	
X2	3.443	-1.991	0.000	8.11%	3.000	4.000	4.000
185.000	1.425	3.135	5.000	3.78%	4.000	4.000	
X3	3.416	-1.954	0.000	8.11%	3.000	4.000	4.000
185.000	1.421	2.983	5.000	3.24%	4.000	4.000	

X4		3.438	-2.038	0.000	8.11%	3.000	4.000
4.000							
	185.000	1.381	3.376	5.000	3.24%	4.000	4.000
X5		3.346	-1.770	0.000	8.11%	3.000	3.000
4.000							
	185.000	1.415	2.613	5.000	4.32%	4.000	4.000
X6		2.978	-0.901	0.000	12.43%	2.000	3.000
3.000							
	185.000	1.902	0.336	5.000	10.27%	3.000	4.000
X7		3.146	-1.003	0.000	11.89%	2.000	3.000
3.000							
	185.000	2.060	0.282	5.000	12.97%	4.000	4.000
X8		2.611	-0.531	0.000	12.97%	2.000	3.000
3.000							
	185.000	1.784	-0.204	5.000	5.95%	3.000	4.000
X9		2.789	-0.602	0.000	11.35%	2.000	3.000
3.000							
	185.000	1.874	-0.309	5.000	6.49%	3.000	4.000
X10		2.822	-0.690	0.000	11.35%	2.000	3.000
3.000							
	185.000	1.855	-0.182	5.000	6.49%	3.000	4.000
AGE		41.330	-0.694	0.000	20.00%	0.000	39.000
47.000							
	185.000	563.270	-0.747	79.000	0.54%	53.000	64.000

UNIVARIATE HIGHER-ORDER MOMENT DESCRIPTIVE STATISTICS FOR FEMALE

Variable/	Mean/	Skewness/	Minimum/	% with		Percentile
s						
Sample Size	Variance	Kurtosis	Maximum	Min/Max	20%/60%	40%/80%
Median						
ENGAGE	10.790	1.674	0.000	11.31%	3.000	7.000
7.000						
1194.000	101.060	3.322	50.000	1.93%	10.000	18.000
PEB	4.532	-2.635	0.000	2.68%	4.000	5.000
5.000						
1194.000	1.174	6.792	5.000	79.31%	5.000	5.000
PEBP	0.843	17.854	0.000	33.58%	0.000	0.200
0.500						
1194.000	15.023	394.799	100.000	0.08%	0.500	1.000
X1	3.415	-1.848	0.000	7.62%	3.000	4.000
4.000						
1194.000	1.449	2.815	6.000	1.17%	4.000	4.000
X2	3.420	-2.104	0.000	7.71%	3.000	4.000
4.000						
1194.000	1.341	3.416	5.000	1.17%	4.000	4.000
X3	3.396	-2.034	0.000	7.96%	3.000	4.000
4.000						
1194.000	1.373	3.151	5.000	1.42%	4.000	4.000
X4	3.430	-2.154	0.000	7.71%	3.000	4.000
4.000						
1194.000	1.315	3.654	5.000	1.09%	4.000	4.000
X5	3.402	-1.946	0.000	7.87%	3.000	4.000
4.000						
1194.000	1.369	3.129	5.000	3.35%	4.000	4.000
X6	3.126	-1.073	0.000	9.38%	3.000	3.000
3.000						
1194.000	1.570	1.285	5.000	10.55%	3.000	4.000
X7	3.296	-1.083	0.000	9.21%	3.000	3.000
4.000						
1194.000	1.825	0.832	5.000	15.83%	4.000	4.000

X8		2.722	-0.679	0.000	9.88%	2.000	3.000
3.000							
	1194.000	1.487	0.468	5.000	5.70%	3.000	4.000
X9		2.969	-0.872	0.000	9.21%	2.000	3.000
3.000							
	1194.000	1.633	0.351	5.000	6.03%	3.000	4.000
X10		3.047	-0.850	0.000	9.21%	2.000	3.000
3.000							
	1194.000	1.747	0.299	5.000	9.30%	4.000	4.000
AGE		42.186	-0.678	0.000	20.77%	0.000	42.000
48.000							
	1194.000	604.669	-0.772	83.000	0.08%	53.000	65.000

THE MODEL ESTIMATION TERMINATED NORMALLY

MODEL FIT INFORMATION

Number of Free Parameters 92

Loglikelihood

H0 Value	-24629.325
H1 Value	-24418.953

Information Criteria

Akaike (AIC)	49442.650
Bayesian (BIC)	49923.728
Sample-Size Adjusted BIC (n* = (n + 2) / 24)	49631.481

Chi-Square Test of Model Fit

Value	420.744
Degrees of Freedom	142
P-Value	0.0000

Chi-Square Contribution From Each Group

MALE	122.526
FEMALE	298.217

RMSEA (Root Mean Square Error Of Approximation)

Estimate	0.053	
90 Percent C.I.	0.048	0.059
Probability RMSEA <= .05	0.169	

CFI/TLI

CFI	0.984
TLI	0.980

Chi-Square Test of Model Fit for the Baseline Model

Value	18161.729
Degrees of Freedom	182
P-Value	0.0000

SRMR (Standardized Root Mean Square Residual)

Value 0.025

MODEL RESULTS

	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
Group MALE				
DNORMS BY				
X9	1.000	0.000	999.000	999.000
X10	1.048	0.022	48.235	0.000
INORMS BY				
X6	1.000	0.000	999.000	999.000
X7	1.094	0.022	50.643	0.000
X8	0.929	0.021	44.958	0.000
EFFS BY				
X1	1.000	0.000	999.000	999.000
X3	1.047	0.018	58.205	0.000
X5	1.010	0.019	53.333	0.000
EFFC BY				
X2	1.000	0.000	999.000	999.000
X4	1.000	0.009	115.262	0.000
PEBG BY				
PEB	1.000	0.000	999.000	999.000
PEBP	0.767	0.230	3.337	0.001
EFFS ON				
DNORMS	-0.243	0.367	-0.661	0.509
INORMS	0.776	0.375	2.070	0.038
EFFC ON				
EFFS	1.050	0.035	29.743	0.000
PEBG ON				
EFFS	0.672	0.723	0.930	0.352
EFFC	-0.565	0.659	-0.857	0.391
INORMS	-0.243	0.462	-0.527	0.598
DNORMS	0.423	0.432	0.978	0.328
DNORMS ON				
ENGAGE	0.027	0.008	3.384	0.001
INORMS ON				
ENGAGE	0.026	0.008	3.333	0.001
EFFS ON				
ENGAGE	0.016	0.006	2.524	0.012
EFFC ON				
ENGAGE	-0.003	0.003	-1.075	0.282
PEBG ON				
ENGAGE	0.017	0.008	2.164	0.030
AGE	0.005	0.003	1.602	0.109

ENGAGE ON				
AGE	-0.062	0.035	-1.783	0.075
INORMS WITH				
DNORMS	1.280	0.146	8.741	0.000
Intercepts				
ENGAGE	14.431	1.659	8.697	0.000
PEB	3.897	0.189	20.604	0.000
PEBP	0.407	0.218	1.867	0.062
X1	3.067	0.114	26.859	0.000
X2	3.106	0.120	25.965	0.000
X3	3.032	0.119	25.535	0.000
X4	3.114	0.120	26.035	0.000
X5	3.043	0.115	26.473	0.000
X6	2.677	0.130	20.567	0.000
X7	2.805	0.142	19.759	0.000
X8	2.308	0.121	19.053	0.000
X9	2.447	0.132	18.536	0.000
X10	2.494	0.137	18.152	0.000
DNORMS	0.000	0.000	999.000	999.000
INORMS	0.000	0.000	999.000	999.000
EFFS	0.000	0.000	999.000	999.000
EFFC	0.000	0.000	999.000	999.000
PEBG	0.000	0.000	999.000	999.000
Residual Variances				
ENGAGE	126.302	13.132	9.618	0.000
PEB	1.165	0.364	3.200	0.001
PEBP	10.494	1.112	9.435	0.000
X1	0.419	0.049	8.584	0.000
X2	0.088	0.016	5.655	0.000
X3	0.143	0.022	6.375	0.000
X4	0.080	0.015	5.286	0.000
X5	0.272	0.034	8.084	0.000
X6	0.520	0.069	7.592	0.000
X7	0.410	0.061	6.728	0.000
X8	0.496	0.064	7.776	0.000
X9	0.450	0.062	7.293	0.000
X10	0.236	0.051	4.656	0.000
DNORMS	1.363	0.163	8.378	0.000
INORMS	1.320	0.157	8.410	0.000
EFFS	0.665	0.088	7.556	0.000
EFFC	0.052	0.019	2.651	0.008
PEBG	0.003	0.346	0.009	0.993
Group FEMALE				
DNORMS BY				
X9	1.000	0.000	999.000	999.000
X10	1.048	0.022	48.235	0.000
INORMS BY				
X6	1.000	0.000	999.000	999.000
X7	1.094	0.022	50.643	0.000
X8	0.929	0.021	44.958	0.000
EFFS BY				
X1	1.000	0.000	999.000	999.000
X3	1.047	0.018	58.205	0.000
X5	1.010	0.019	53.333	0.000
EFFC BY				

X2	1.000	0.000	999.000	999.000
X4	1.000	0.009	115.262	0.000
PEBG BY				
PEB	1.000	0.000	999.000	999.000
PEBP	0.767	0.230	3.337	0.001
EFFS ON				
DNORMS	0.037	0.112	0.328	0.743
INORMS	0.625	0.114	5.474	0.000
EFFC ON				
EFFS	1.032	0.019	55.151	0.000
PEBG ON				
EFFS	0.279	0.211	1.324	0.186
EFFC	-0.007	0.192	-0.035	0.972
INORMS	0.116	0.146	0.795	0.427
DNORMS	0.057	0.138	0.413	0.680
DNORMS ON				
ENGAGE	0.027	0.003	7.978	0.000
INORMS ON				
ENGAGE	0.031	0.003	9.352	0.000
EFFS ON				
ENGAGE	0.014	0.002	5.732	0.000
EFFC ON				
ENGAGE	0.000	0.001	0.219	0.826
PEBG ON				
ENGAGE	0.004	0.003	1.275	0.202
AGE	0.000	0.001	0.252	0.801
ENGAGE ON				
AGE	0.005	0.012	0.408	0.684
INORMS WITH				
DNORMS	1.130	0.054	21.086	0.000
Intercepts				
ENGAGE	10.586	0.578	18.326	0.000
PEB	3.897	0.189	20.604	0.000
PEBP	0.407	0.218	1.867	0.062
X1	3.067	0.114	26.859	0.000
X2	3.106	0.120	25.965	0.000
X3	3.032	0.119	25.535	0.000
X4	3.114	0.120	26.035	0.000
X5	3.043	0.115	26.473	0.000
X6	2.677	0.130	20.567	0.000
X7	2.805	0.142	19.759	0.000
X8	2.308	0.121	19.053	0.000
X9	2.447	0.132	18.536	0.000
X10	2.494	0.137	18.152	0.000
DNORMS	0.233	0.140	1.662	0.097
INORMS	0.117	0.138	0.852	0.394
EFFS	-0.097	0.103	-0.943	0.346
EFFC	-0.049	0.047	-1.038	0.299
PEBG	0.402	0.199	2.015	0.044
Residual Variances				

ENGAGE	101.046	4.136	24.434	0.000
PEB	0.855	0.151	5.672	0.000
PEBP	14.875	0.615	24.199	0.000
X1	0.319	0.015	21.792	0.000
X2	0.073	0.005	15.063	0.000
X3	0.123	0.007	16.943	0.000
X4	0.043	0.004	10.248	0.000
X5	0.202	0.010	20.062	0.000
X6	0.305	0.017	17.610	0.000
X7	0.308	0.019	16.566	0.000
X8	0.406	0.020	20.257	0.000
X9	0.335	0.020	16.372	0.000
X10	0.330	0.021	15.406	0.000
DNORMS	1.219	0.063	19.436	0.000
INORMS	1.168	0.059	19.835	0.000
EFFS	0.514	0.028	18.254	0.000
EFFC	0.056	0.006	8.994	0.000
PEBG	0.101	0.147	0.686	0.493

QUALITY OF NUMERICAL RESULTS

Condition Number for the Information Matrix 0.327E-06
(ratio of smallest to largest eigenvalue)

STANDARDIZED MODEL RESULTS

STDYX Standardization

	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
Group MALE				
DNORMS BY				
X9	0.874	0.019	46.317	0.000
X10	0.934	0.016	60.070	0.000
INORMS BY				
X6	0.855	0.021	41.060	0.000
X7	0.897	0.017	53.199	0.000
X8	0.843	0.022	37.895	0.000
EFFS BY				
X1	0.858	0.019	45.504	0.000
X3	0.949	0.009	101.530	0.000
X5	0.902	0.014	64.477	0.000
EFFC BY				
X2	0.968	0.006	151.659	0.000
X4	0.971	0.006	160.738	0.000
PEBG BY				
PEB	0.380	0.331	1.147	0.251
PEBP	0.104	0.096	1.090	0.276
EFFS ON				
DNORMS	-0.271	0.409	-0.662	0.508
INORMS	0.852	0.406	2.099	0.036
EFFC ON				

EFFS	0.989	0.012	82.161	0.000
PEBG ON				
EFFS	1.640	2.241	0.732	0.464
EFFC	-1.463	2.103	-0.696	0.487
INORMS	-0.652	1.367	-0.477	0.634
DNORMS	1.152	1.548	0.744	0.457
DNORMS ON				
ENGAGE	0.255	0.073	3.497	0.000
INORMS ON				
ENGAGE	0.251	0.073	3.447	0.001
EFFS ON				
ENGAGE	0.163	0.064	2.538	0.011
EFFC ON				
ENGAGE	-0.030	0.028	-1.072	0.284
PEBG ON				
ENGAGE	0.438	0.428	1.023	0.306
AGE	0.286	0.294	0.973	0.331
ENGAGE ON				
AGE	-0.130	0.072	-1.799	0.072
INORMS WITH				
DNORMS	0.954	0.018	51.763	0.000
Intercepts				
ENGAGE	1.273	0.151	8.442	0.000
PEB	3.340	0.268	12.465	0.000
PEBP	0.125	0.067	1.852	0.064
X1	2.433	0.158	15.371	0.000
X2	2.619	0.187	14.031	0.000
X3	2.540	0.183	13.860	0.000
X4	2.634	0.188	13.993	0.000
X5	2.514	0.171	14.695	0.000
X6	1.927	0.142	13.594	0.000
X7	1.937	0.151	12.795	0.000
X8	1.764	0.135	13.087	0.000
X9	1.771	0.140	12.615	0.000
X10	1.840	0.153	11.988	0.000
DNORMS	0.000	0.000	999.000	999.000
INORMS	0.000	0.000	999.000	999.000
EFFS	0.000	0.000	999.000	999.000
EFFC	0.000	0.000	999.000	999.000
PEBG	0.000	0.000	999.000	999.000
Residual Variances				
ENGAGE	0.983	0.019	52.312	0.000
PEB	0.856	0.252	3.400	0.001
PEBP	0.989	0.020	49.537	0.000
X1	0.264	0.032	8.156	0.000
X2	0.063	0.012	5.070	0.000
X3	0.100	0.018	5.649	0.000
X4	0.057	0.012	4.851	0.000
X5	0.186	0.025	7.348	0.000
X6	0.270	0.036	7.578	0.000
X7	0.195	0.030	6.456	0.000
X8	0.290	0.037	7.721	0.000
X9	0.236	0.033	7.148	0.000

X10	0.129	0.029	4.429	0.000
DNORMS	0.935	0.037	25.186	0.000
INORMS	0.937	0.037	25.565	0.000
EFFS	0.568	0.067	8.508	0.000
EFFC	0.039	0.015	2.579	0.010
PEBG	0.016	1.733	0.009	0.992

Group FEMALE

DNORMS BY				
X9	0.891	0.008	113.308	0.000
X10	0.901	0.008	120.001	0.000
INORMS BY				
X6	0.897	0.007	127.839	0.000
X7	0.912	0.006	143.454	0.000
X8	0.853	0.009	96.476	0.000
EFFS BY				
X1	0.884	0.007	131.101	0.000
X3	0.954	0.003	291.835	0.000
X5	0.923	0.005	191.402	0.000
EFFC BY				
X2	0.973	0.002	457.966	0.000
X4	0.984	0.002	562.707	0.000
PEBG BY				
PEB	0.520	0.122	4.247	0.000
PEBP	0.111	0.037	3.016	0.003
EFFS ON				
DNORMS	0.039	0.119	0.328	0.743
INORMS	0.658	0.118	5.559	0.000
EFFC ON				
EFFS	0.977	0.004	222.510	0.000
PEBG ON				
EFFS	0.530	0.420	1.263	0.207
EFFC	-0.014	0.384	-0.035	0.972
INORMS	0.232	0.295	0.787	0.432
DNORMS	0.115	0.281	0.410	0.682
DNORMS ON				
ENGAGE	0.239	0.029	8.238	0.000
INORMS ON				
ENGAGE	0.274	0.028	9.783	0.000
EFFS ON				
ENGAGE	0.129	0.022	5.753	0.000
EFFC ON				
ENGAGE	0.002	0.010	0.219	0.826
PEBG ON				
ENGAGE	0.068	0.055	1.224	0.221
AGE	0.013	0.050	0.251	0.802
ENGAGE ON				
AGE	0.012	0.029	0.408	0.684

INORMS WITH				
DNORMS	0.947	0.008	126.117	0.000
Intercepts				
ENGAGE	1.053	0.062	17.078	0.000
PEB	3.601	0.190	18.938	0.000
PEBP	0.105	0.056	1.860	0.063
X1	2.540	0.108	23.416	0.000
X2	2.680	0.117	22.920	0.000
X3	2.588	0.114	22.617	0.000
X4	2.717	0.118	22.966	0.000
X5	2.606	0.112	23.194	0.000
X6	2.138	0.113	18.847	0.000
X7	2.079	0.114	18.280	0.000
X8	1.887	0.107	17.648	0.000
X9	1.917	0.111	17.225	0.000
X10	1.885	0.111	17.009	0.000
DNORMS	0.205	0.124	1.657	0.098
INORMS	0.105	0.123	0.850	0.395
EFFS	-0.091	0.097	-0.945	0.345
EFFC	-0.043	0.042	-1.038	0.299
PEBG	0.715	0.392	1.824	0.068
Residual Variances				
ENGAGE	1.000	0.001	1464.666	0.000
PEB	0.730	0.127	5.733	0.000
PEBP	0.988	0.008	120.564	0.000
X1	0.219	0.012	18.379	0.000
X2	0.054	0.004	13.075	0.000
X3	0.090	0.006	14.395	0.000
X4	0.033	0.003	9.502	0.000
X5	0.148	0.009	16.593	0.000
X6	0.195	0.013	15.458	0.000
X7	0.169	0.012	14.594	0.000
X8	0.272	0.015	17.995	0.000
X9	0.206	0.014	14.690	0.000
X10	0.189	0.014	13.949	0.000
DNORMS	0.943	0.014	67.945	0.000
INORMS	0.925	0.015	60.348	0.000
EFFS	0.451	0.022	20.934	0.000
EFFC	0.044	0.005	8.542	0.000
PEBG	0.318	0.316	1.006	0.314

STDY Standardization

	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
Group MALE				
DNORMS BY				
X9	0.874	0.019	46.317	0.000
X10	0.934	0.016	60.070	0.000
INORMS BY				
X6	0.855	0.021	41.060	0.000
X7	0.897	0.017	53.199	0.000
X8	0.843	0.022	37.895	0.000
EFFS BY				
X1	0.858	0.019	45.504	0.000
X3	0.949	0.009	101.530	0.000

X5	0.902	0.014	64.477	0.000
EFFC BY				
X2	0.968	0.006	151.659	0.000
X4	0.971	0.006	160.738	0.000
PEBG BY				
PEB	0.380	0.331	1.147	0.251
PEBP	0.104	0.096	1.090	0.276
EFFS ON				
DNORMS	-0.271	0.409	-0.662	0.508
INORMS	0.852	0.406	2.099	0.036
EFFC ON				
EFFS	0.989	0.012	82.161	0.000
PEBG ON				
EFFS	1.640	2.241	0.732	0.464
EFFC	-1.463	2.103	-0.696	0.487
INORMS	-0.652	1.367	-0.477	0.634
DNORMS	1.152	1.548	0.744	0.457
DNORMS ON				
ENGAGE	0.255	0.073	3.497	0.000
INORMS ON				
ENGAGE	0.251	0.073	3.447	0.001
EFFS ON				
ENGAGE	0.163	0.064	2.538	0.011
EFFC ON				
ENGAGE	-0.030	0.028	-1.072	0.284
PEBG ON				
ENGAGE	0.438	0.428	1.023	0.306
AGE	0.012	0.012	0.974	0.330
ENGAGE ON				
AGE	-0.005	0.003	-1.806	0.071
INORMS WITH				
DNORMS	0.954	0.018	51.763	0.000
Intercepts				
ENGAGE	1.273	0.151	8.442	0.000
PEB	3.340	0.268	12.465	0.000
PEBP	0.125	0.067	1.852	0.064
X1	2.433	0.158	15.371	0.000
X2	2.619	0.187	14.031	0.000
X3	2.540	0.183	13.860	0.000
X4	2.634	0.188	13.993	0.000
X5	2.514	0.171	14.695	0.000
X6	1.927	0.142	13.594	0.000
X7	1.937	0.151	12.795	0.000
X8	1.764	0.135	13.087	0.000
X9	1.771	0.140	12.615	0.000
X10	1.840	0.153	11.988	0.000
DNORMS	0.000	0.000	999.000	999.000
INORMS	0.000	0.000	999.000	999.000
EFFS	0.000	0.000	999.000	999.000
EFFC	0.000	0.000	999.000	999.000

PEBG	0.000	0.000	999.000	999.000

Residual Variances

ENGAGE	0.983	0.019	52.312	0.000
PEB	0.856	0.252	3.400	0.001
PEBP	0.989	0.020	49.537	0.000
X1	0.264	0.032	8.156	0.000
X2	0.063	0.012	5.070	0.000
X3	0.100	0.018	5.649	0.000
X4	0.057	0.012	4.851	0.000
X5	0.186	0.025	7.348	0.000
X6	0.270	0.036	7.578	0.000
X7	0.195	0.030	6.456	0.000
X8	0.290	0.037	7.721	0.000
X9	0.236	0.033	7.148	0.000
X10	0.129	0.029	4.429	0.000
DNORMS	0.935	0.037	25.186	0.000
INORMS	0.937	0.037	25.565	0.000
EFFS	0.568	0.067	8.508	0.000
EFFC	0.039	0.015	2.579	0.010
PEBG	0.016	1.733	0.009	0.992

Group FEMALE

DNORMS BY

X9	0.891	0.008	113.308	0.000
X10	0.901	0.008	120.001	0.000

INORMS BY

X6	0.897	0.007	127.839	0.000
X7	0.912	0.006	143.454	0.000
X8	0.853	0.009	96.476	0.000

EFFS BY

X1	0.884	0.007	131.101	0.000
X3	0.954	0.003	291.835	0.000
X5	0.923	0.005	191.402	0.000

EFFC BY

X2	0.973	0.002	457.966	0.000
X4	0.984	0.002	562.707	0.000

PEBG BY

PEB	0.520	0.122	4.247	0.000
PEBP	0.111	0.037	3.016	0.003

EFFS ON

DNORMS	0.039	0.119	0.328	0.743
INORMS	0.658	0.118	5.559	0.000

EFFC ON

EFFS	0.977	0.004	222.510	0.000

PEBG ON

EFFS	0.530	0.420	1.263	0.207
EFFC	-0.014	0.384	-0.035	0.972
INORMS	0.232	0.295	0.787	0.432
DNORMS	0.115	0.281	0.410	0.682

DNORMS ON

ENGAGE	0.239	0.029	8.238	0.000

INORMS ON

ENGAGE	0.274	0.028	9.783	0.000
EFFS ON				
ENGAGE	0.129	0.022	5.753	0.000
EFFC ON				
ENGAGE	0.002	0.010	0.219	0.826
PEBG ON				
ENGAGE	0.068	0.055	1.224	0.221
AGE	0.001	0.002	0.251	0.802
ENGAGE ON				
AGE	0.000	0.001	0.408	0.684
INORMS WITH				
DNORMS	0.947	0.008	126.117	0.000
Intercepts				
ENGAGE	1.053	0.062	17.078	0.000
PEB	3.601	0.190	18.938	0.000
PEBP	0.105	0.056	1.860	0.063
X1	2.540	0.108	23.416	0.000
X2	2.680	0.117	22.920	0.000
X3	2.588	0.114	22.617	0.000
X4	2.717	0.118	22.966	0.000
X5	2.606	0.112	23.194	0.000
X6	2.138	0.113	18.847	0.000
X7	2.079	0.114	18.280	0.000
X8	1.887	0.107	17.648	0.000
X9	1.917	0.111	17.225	0.000
X10	1.885	0.111	17.009	0.000
DNORMS	0.205	0.124	1.657	0.098
INORMS	0.105	0.123	0.850	0.395
EFFS	-0.091	0.097	-0.945	0.345
EFFC	-0.043	0.042	-1.038	0.299
PEBG	0.715	0.392	1.824	0.068
Residual Variances				
ENGAGE	1.000	0.001	1464.666	0.000
PEB	0.730	0.127	5.733	0.000
PEBP	0.988	0.008	120.564	0.000
X1	0.219	0.012	18.379	0.000
X2	0.054	0.004	13.075	0.000
X3	0.090	0.006	14.395	0.000
X4	0.033	0.003	9.502	0.000
X5	0.148	0.009	16.593	0.000
X6	0.195	0.013	15.458	0.000
X7	0.169	0.012	14.594	0.000
X8	0.272	0.015	17.995	0.000
X9	0.206	0.014	14.690	0.000
X10	0.189	0.014	13.949	0.000
DNORMS	0.943	0.014	67.945	0.000
INORMS	0.925	0.015	60.348	0.000
EFFS	0.451	0.022	20.934	0.000
EFFC	0.044	0.005	8.542	0.000
PEBG	0.318	0.316	1.006	0.314

STD Standardization

	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value

Group MALE

DNORMS BY				
X9	1.207	0.071	16.909	0.000
X10	1.266	0.074	17.174	0.000
INORMS BY				
X6	1.187	0.070	16.923	0.000
X7	1.299	0.076	17.093	0.000
X8	1.103	0.066	16.755	0.000
EFFS BY				
X1	1.082	0.062	17.556	0.000
X3	1.133	0.063	17.993	0.000
X5	1.092	0.061	17.806	0.000
EFFC BY				
X2	1.148	0.062	18.562	0.000
X4	1.148	0.062	18.582	0.000
PEBG BY				
PEB	0.443	0.387	1.145	0.252
PEBP	0.340	0.311	1.091	0.275
EFFS ON				
DNORMS	-0.271	0.409	-0.662	0.508
INORMS	0.852	0.406	2.099	0.036
EFFC ON				
EFFS	0.989	0.012	82.161	0.000
PEBG ON				
EFFS	1.640	2.241	0.732	0.464
EFFC	-1.463	2.103	-0.696	0.487
INORMS	-0.652	1.367	-0.477	0.634
DNORMS	1.152	1.548	0.744	0.457
DNORMS ON				
ENGAGE	0.022	0.006	3.548	0.000
INORMS ON				
ENGAGE	0.022	0.006	3.496	0.000
EFFS ON				
ENGAGE	0.014	0.006	2.556	0.011
EFFC ON				
ENGAGE	-0.003	0.002	-1.073	0.283
PEBG ON				
ENGAGE	0.039	0.038	1.023	0.306
AGE	0.012	0.012	0.974	0.330
ENGAGE ON				
AGE	-0.062	0.035	-1.783	0.075
INORMS WITH				
DNORMS	0.954	0.018	51.763	0.000
Intercepts				
ENGAGE	14.431	1.659	8.697	0.000
PEB	3.897	0.189	20.604	0.000

PEBP	0.407	0.218	1.867	0.062
X1	3.067	0.114	26.859	0.000
X2	3.106	0.120	25.965	0.000
X3	3.032	0.119	25.535	0.000
X4	3.114	0.120	26.035	0.000
X5	3.043	0.115	26.473	0.000
X6	2.677	0.130	20.567	0.000
X7	2.805	0.142	19.759	0.000
X8	2.308	0.121	19.053	0.000
X9	2.447	0.132	18.536	0.000
X10	2.494	0.137	18.152	0.000
DNORMS	0.000	0.000	999.000	999.000
INORMS	0.000	0.000	999.000	999.000
EFFS	0.000	0.000	999.000	999.000
EFFC	0.000	0.000	999.000	999.000
PEBG	0.000	0.000	999.000	999.000

Residual Variances

ENGAGE	126.302	13.132	9.618	0.000
PEB	1.165	0.364	3.200	0.001
PEBP	10.494	1.112	9.435	0.000
X1	0.419	0.049	8.584	0.000
X2	0.088	0.016	5.655	0.000
X3	0.143	0.022	6.375	0.000
X4	0.080	0.015	5.286	0.000
X5	0.272	0.034	8.084	0.000
X6	0.520	0.069	7.592	0.000
X7	0.410	0.061	6.728	0.000
X8	0.496	0.064	7.776	0.000
X9	0.450	0.062	7.293	0.000
X10	0.236	0.051	4.656	0.000
DNORMS	0.935	0.037	25.186	0.000
INORMS	0.937	0.037	25.565	0.000
EFFS	0.568	0.067	8.508	0.000
EFFC	0.039	0.015	2.579	0.010
PEBG	0.016	1.733	0.009	0.992

Group FEMALE

DNORMS BY

X9	1.137	0.029	39.143	0.000
X10	1.192	0.030	39.813	0.000

INORMS BY

X6	1.124	0.028	39.855	0.000
X7	1.230	0.030	40.887	0.000
X8	1.044	0.028	37.121	0.000

EFFS BY

X1	1.067	0.027	39.526	0.000
X3	1.118	0.025	44.673	0.000
X5	1.078	0.025	42.292	0.000

EFFC BY

X2	1.127	0.024	46.347	0.000
X4	1.127	0.024	47.232	0.000

PEBG BY

PEB	0.563	0.134	4.205	0.000
PEBP	0.431	0.144	3.000	0.003

EFFS ON

DNORMS	0.039	0.119	0.328	0.743

INORMS	0.658	0.118	5.559	0.000
EFFC ON				
EFFS	0.977	0.004	222.510	0.000
PEBG ON				
EFFS	0.530	0.420	1.263	0.207
EFFC	-0.014	0.384	-0.035	0.972
INORMS	0.232	0.295	0.787	0.432
DNORMS	0.115	0.281	0.410	0.682
DNORMS ON				
ENGAGE	0.024	0.003	8.343	0.000
INORMS ON				
ENGAGE	0.027	0.003	9.954	0.000
EFFS ON				
ENGAGE	0.013	0.002	5.785	0.000
EFFC ON				
ENGAGE	0.000	0.001	0.219	0.826
PEBG ON				
ENGAGE	0.007	0.006	1.224	0.221
AGE	0.001	0.002	0.251	0.802
ENGAGE ON				
AGE	0.005	0.012	0.408	0.684
INORMS WITH				
DNORMS	0.947	0.008	126.117	0.000
Intercepts				
ENGAGE	10.586	0.578	18.326	0.000
PEB	3.897	0.189	20.604	0.000
PEBP	0.407	0.218	1.867	0.062
X1	3.067	0.114	26.859	0.000
X2	3.106	0.120	25.965	0.000
X3	3.032	0.119	25.535	0.000
X4	3.114	0.120	26.035	0.000
X5	3.043	0.115	26.473	0.000
X6	2.677	0.130	20.567	0.000
X7	2.805	0.142	19.759	0.000
X8	2.308	0.121	19.053	0.000
X9	2.447	0.132	18.536	0.000
X10	2.494	0.137	18.152	0.000
DNORMS	0.205	0.124	1.657	0.098
INORMS	0.105	0.123	0.850	0.395
EFFS	-0.091	0.097	-0.945	0.345
EFFC	-0.043	0.042	-1.038	0.299
PEBG	0.715	0.392	1.824	0.068
Residual Variances				
ENGAGE	101.046	4.136	24.434	0.000
PEB	0.855	0.151	5.672	0.000
PEBP	14.875	0.615	24.199	0.000
X1	0.319	0.015	21.792	0.000
X2	0.073	0.005	15.063	0.000
X3	0.123	0.007	16.943	0.000
X4	0.043	0.004	10.248	0.000
X5	0.202	0.010	20.062	0.000
X6	0.305	0.017	17.610	0.000

X7	0.308	0.019	16.566	0.000
X8	0.406	0.020	20.257	0.000
X9	0.335	0.020	16.372	0.000
X10	0.330	0.021	15.406	0.000
DNORMS	0.943	0.014	67.945	0.000
INORMS	0.925	0.015	60.348	0.000
EFFS	0.451	0.022	20.934	0.000
EFFC	0.044	0.005	8.542	0.000
PEBG	0.318	0.316	1.006	0.314

R-SQUARE

Group MALE

Observed Variable	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
ENGAGE	0.017	0.019	0.899	0.368
PEB	0.144	0.252	0.573	0.566
PEBP	0.011	0.020	0.545	0.586
X1	0.736	0.032	22.752	0.000
X2	0.937	0.012	75.829	0.000
X3	0.900	0.018	50.765	0.000
X4	0.943	0.012	80.369	0.000
X5	0.814	0.025	32.239	0.000
X6	0.730	0.036	20.530	0.000
X7	0.805	0.030	26.599	0.000
X8	0.710	0.037	18.948	0.000
X9	0.764	0.033	23.159	0.000
X10	0.871	0.029	30.035	0.000

Latent Variable	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
DNORMS	0.065	0.037	1.748	0.080
INORMS	0.063	0.037	1.724	0.085
EFFS	0.432	0.067	6.458	0.000
EFFC	0.961	0.015	63.433	0.000
PEBG	0.984	1.733	0.568	0.570

Group FEMALE

Observed Variable	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
ENGAGE	0.000	0.001	0.204	0.838
PEB	0.270	0.127	2.124	0.034
PEBP	0.012	0.008	1.508	0.132
X1	0.781	0.012	65.550	0.000
X2	0.946	0.004	228.983	0.000
X3	0.910	0.006	145.917	0.000
X4	0.967	0.003	281.354	0.000
X5	0.852	0.009	95.701	0.000
X6	0.805	0.013	63.920	0.000
X7	0.831	0.012	71.727	0.000
X8	0.728	0.015	48.238	0.000
X9	0.794	0.014	56.654	0.000
X10	0.811	0.014	60.000	0.000

Latent Variable	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value

DNORMS	0.057	0.014	4.119	0.000
INORMS	0.075	0.015	4.892	0.000
EFFS	0.549	0.022	25.471	0.000
EFFC	0.956	0.005	184.631	0.000
PEBG	0.682	0.316	2.159	0.031

MODEL MODIFICATION INDICES

NOTE: Modification indices for direct effects of observed dependent variables regressed on covariates may not be included. To include these, request MODINDICES (ALL).

Minimum M.I. value for printing the modification index 10.000

		M.I.	E.P.C.	Std E.P.C.	StdYX E.P.C.
Group MALE					
WITH Statements					
X5	WITH X4	12.613	0.060	0.060	0.406
X8	WITH X6	11.041	0.164	0.164	0.323
X9	WITH X7	24.560	-0.230	-0.230	-0.537
X10	WITH X6	14.630	-0.162	-0.162	-0.462
X10	WITH X7	43.754	0.282	0.282	0.907
Gro					
X4	WITH X1	10.112	-0.017	-0.017	-0.149
X5	WITH X1	17.132	0.037	0.037	0.146
X8	WITH X6	29.265	0.080	0.080	0.226
X8	WITH X7	10.636	-0.052	-0.052	-0.147
X9	WITH X6	33.976	0.081	0.081	0.252
X9	WITH X7	68.062	-0.121	-0.121	-0.375
X10	WITH X6	102.256	-0.143	-0.143	-0.450
X10	WITH X7	161.419	0.190	0.190	0.597

DIAGRAM INFORMATION

Use View Diagram under the Diagram menu in the Mplus Editor to view the diagram.
If running Mplus from the Mplus Diagrammer, the diagram opens automatically.

Diagram output
c:\users\serah\documents\research\dissertation\mplus data\peb2cgroups.dgm

Beginning Time: 12:27:32
Ending Time: 12:27:32
Elaps

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Mplus VERSION 8.11
MUTHEN & MUTHEN
12/22/2024   1:08 PM

INPUT INSTRUCTIONS

  TITLE:

  DATA:
    ! enter the name of the data set
    FILE = "C:\Users\serah\Documents\Research\Dissertation\groups2.csv";

  VARIABLE:
    ! enter the names of the variables in the data set
    NAMES = age engage barriers PEB PEBP x1-x10 group;
      USEVARIABLES = age engage PEB PEBP x1-x10 group;
      GROUPING IS group (1=NCNPF 2=CANPS 3=other);
  DEFINE:

  MODEL:

      dnorms by x9 x10;
    inorms by x6-x8;
    effs by x1 x3 x5;
    effc by x2 x4;
      PEBG by PEB PEBP;
    engage on age;
    dnorms on engage;
    inorms on engage;
    effs on engage;
    effc on engage;
    PEBG ON effs effc inorms dnorms;
    effc on effs;
      PEBG on engage;
      PEBG on age;
      inorms WITH dnorms;
      effs on dnorms inorms;
     !Model Indirect: PEBG IND inorms;
     !PEBG IND dnorms;


  OUTPUT:
  STANDARDIZED;
  MOD;



*** WARNING
  Data set contains unknown or missing values for GROUPING,
  PATTERN, COHORT, CLUSTER and/or STRATIFICATION variables.
  Number of cases with unknown or missing values:  143
   1 WARNING(S) FOUND IN THE INPUT INSTRUCTIONS




SUMMARY OF ANALYSIS

Number of groups                         3
Number of observations
   Group NCNPF                           293
   Group CANPS                           167
   Group OTHER                           917
```

```
   Total sample size                                          1377

Number of dependent variables                                   13
Number of independent variables                                  1
Number of continuous latent variables                            5

Observed dependent variables

  Continuous
   ENGAGE      PEB         PEBP        X1          X2          X3
   X4          X5          X6          X7          X8          X9
   X10

Observed independent variables
   AGE

Continuous latent variables
   DNORMS      INORMS      EFFS        EFFC        PEBG

Variables with special functions

  Grouping variable     GROUP

Estimator                                                       ML
Information matrix                                        OBSERVED
Maximum number of iterations                                  1000
Convergence criterion                                    0.500D-04
Maximum number of steepest descent iterations                   20

Input data file(s)
  C:\Users\serah\Documents\Research\Dissertation\groups2.csv

Input data format  FREE



UNIVARIATE SAMPLE STATISTICS


     UNIVARIATE HIGHER-ORDER MOMENT DESCRIPTIVE STATISTICS FOR NCNPF

         Variable/         Mean/     Skewness/   Minimum/ % with                Percentile
s
        Sample Size      Variance    Kurtosis    Maximum  Min/Max      20%/60%    40%/80%
   Median

     ENGAGE                9.901       1.408       0.000  6.14%          4.000      6.000
    7.000
            293.000       66.731       2.344      50.000  0.34%         10.000     15.000
     PEB                  4.471      -2.004       0.000  1.02%          4.000      5.000
    5.000
            293.000       1.041       3.641       5.000  74.06%         5.000      5.000
     PEBP                 0.732      10.417       0.000  34.13%         0.000      0.130
    0.500
            293.000       6.985     118.258      35.000  0.34%          0.500      1.000
     X1                   3.457      -1.917       0.000   5.46%         3.000      4.000
    4.000
            293.000       1.149       4.144       6.000   1.37%         4.000      4.000
     X2                   3.532      -2.521       0.000   5.46%         3.000      4.000
    4.000
            293.000       0.993       6.167       5.000   1.37%         4.000      4.000
     X3                   3.447      -2.265       0.000  5.80%          3.000      4.000
    4.000
```

	293.000	1.053	4.969	5.000	1.37%	4.000	4.000
X4		3.532	-2.546	0.000	5.46%	3.000	4.000
4.000							
	293.000	0.972	6.409	5.000	1.37%	4.000	4.000
X5		3.416	-2.071	0.000	5.46%	3.000	3.000
4.000							
	293.000	1.001	4.927	5.000	3.07%	4.000	4.000
X6		3.041	-1.030	0.000	8.19%	3.000	3.000
3.000							
	293.000	1.377	1.513	5.000	7.85%	3.000	4.000
X7		3.119	-0.989	0.000	8.53%	2.000	3.000
3.000							
	293.000	1.607	0.802	5.000	9.22%	4.000	4.000
X8		2.611	-0.632	0.000	8.19%	2.000	3.000
3.000							
	293.000	1.248	0.694	5.000	3.75%	3.000	3.000
X9		2.877	-0.918	0.000	8.19%	2.000	3.000
3.000							
	293.000	1.425	0.453	5.000	2.39%	3.000	4.000
X10		2.843	-0.700	0.000	8.19%	2.000	3.000
3.000							
	293.000	1.525	0.172	5.000	4.78%	3.000	4.000
AGE		41.901	-0.642	0.000	19.80%	18.000	41.000
47.000							
	293.000	589.673	-0.798	79.000	0.34%	53.000	64.000

UNIVARIATE HIGHER-ORDER MOMENT DESCRIPTIVE STATISTICS FOR CANPS

Variable/	Mean/	Skewness/	Minimum/	% with		Percentile
s						
Sample Size	Variance	Kurtosis	Maximum	Min/Max	20%/60%	40%/80%
Median						
ENGAGE	10.970	1.757	0.000	7.78%	4.000	7.000
8.000						
167.000	94.568	3.789	50.000	1.80%	10.000	17.000
PEB	4.503	-2.534	0.000	2.99%	4.000	5.000
5.000						
167.000	1.256	6.131	5.000	78.44%	5.000	5.000
PEBP	0.538	2.718	0.000	45.51%	0.000	0.000
0.500						
167.000	0.560	10.712	5.000	0.60%	0.500	1.000
X1	3.389	-1.623	0.000	7.19%	3.000	4.000
4.000						
167.000	1.531	2.190	6.000	1.80%	4.000	4.000
X2	3.413	-1.941	0.000	7.19%	3.000	4.000
4.000						
167.000	1.404	2.787	5.000	2.40%	4.000	4.000
X3	3.365	-1.888	0.000	7.19%	3.000	4.000
4.000						
167.000	1.382	2.639	5.000	1.80%	4.000	4.000
X4	3.395	-1.972	0.000	7.19%	3.000	4.000
4.000						
167.000	1.353	2.979	5.000	1.80%	4.000	4.000
X5	3.305	-1.681	0.000	7.19%	3.000	3.000
4.000						
167.000	1.374	2.315	5.000	3.59%	4.000	4.000
X6	3.240	-1.144	0.000	9.58%	3.000	3.000
3.000						
167.000	1.655	1.389	5.000	13.77%	4.000	4.000
X7	3.515	-1.323	0.000	9.58%	3.000	4.000
4.000						

	167.000	1.950	1.250	5.000	22.75%	4.000	5.000
X8		2.988	-0.871	0.000	11.98%	2.000	3.000
3.000							
	167.000	1.820	0.533	5.000	11.38%	3.000	4.000
X9		3.042	-0.899	0.000	9.58%	2.000	3.000
3.000							
	167.000	1.729	0.380	5.000	8.38%	4.000	4.000
X10		3.287	-1.175	0.000	9.58%	3.000	3.000
4.000							
	167.000	1.822	0.856	5.000	12.57%	4.000	4.000
AGE		41.497	-0.511	0.000	24.55%	0.000	42.000
46.000							
	167.000	711.723	-1.087	81.000	0.60%	53.000	66.000

UNIVARIATE HIGHER-ORDER MOMENT DESCRIPTIVE STATISTICS FOR OTHER

Variable/	Mean/	Skewness/	Minimum/	% with		Percentile
s						
Sample Size	Variance	Kurtosis	Maximum	Min/Max	20%/60%	40%/80%
Median						
ENGAGE	11.788	1.614	0.000	9.38%	4.000	7.000
9.000						
917.000	115.855	2.797	50.000	2.51%	10.000	20.000
PEB	4.534	-2.669	0.000	2.94%	5.000	5.000
5.000						
917.000	1.213	6.872	5.000	80.15%	5.000	5.000
PEBP	1.011	15.298	0.000	31.30%	0.000	0.300
0.500						
917.000	19.684	294.912	100.000	0.11%	0.670	1.000
X1	3.429	-1.918	0.000	8.07%	3.000	4.000
4.000						
917.000	1.482	2.855	6.000	0.98%	4.000	4.000
X2	3.420	-2.060	0.000	8.18%	3.000	4.000
4.000						
917.000	1.406	3.173	5.000	1.64%	4.000	4.000
X3	3.419	-2.039	0.000	8.40%	3.000	4.000
4.000						
917.000	1.430	3.097	5.000	1.96%	4.000	4.000
X4	3.431	-2.106	0.000	8.18%	3.000	4.000
4.000						
917.000	1.386	3.370	5.000	1.53%	4.000	4.000
X5	3.421	-1.964	0.000	8.40%	3.000	4.000
4.000						
917.000	1.450	2.965	5.000	3.38%	4.000	4.000
X6	3.134	-1.103	0.000	9.71%	3.000	3.000
3.000						
917.000	1.597	1.276	5.000	10.47%	3.000	4.000
X7	3.309	-1.107	0.000	9.38%	3.000	3.000
4.000						
917.000	1.832	0.895	5.000	16.25%	4.000	4.000
X8	2.724	-0.664	0.000	10.03%	2.000	3.000
3.000						
917.000	1.515	0.397	5.000	5.78%	3.000	4.000
X9	2.957	-0.818	0.000	9.49%	2.000	3.000
3.000						
917.000	1.685	0.236	5.000	6.76%	3.000	4.000
X10	3.043	-0.833	0.000	9.49%	2.000	3.000
3.000						
917.000	1.779	0.260	5.000	9.81%	4.000	4.000
AGE	41.475	-0.699	0.000	20.39%	0.000	42.000
47.000						

917.000	571.288	-0.728	81.000	0.22%	52.000	63.000

THE MODEL ESTIMATION TERMINATED NORMALLY

WARNING: THE LATENT VARIABLE COVARIANCE MATRIX (PSI) IN GROUP CANPS IS NOT POSITIVE DEFINITE. THIS COULD INDICATE A NEGATIVE VARIANCE/ RESIDUAL VARIANCE FOR A LATENT VARIABLE, A CORRELATION GREATER OR EQUAL TO ONE BETWEEN TWO LATENT VARIABLES, OR A LINEAR DEPENDENCY AMONG MORE THAN TWO LATENT VARIABLES. CHECK THE TECH4 OUTPUT FOR MORE INFORMATION. PROBLEM INVOLVING VARIABLE PEBG.

MODEL FIT INFORMATION

Number of Free Parameters 131

Loglikelihood

H0 Value	-24060.892
H1 Value	-23788.341

Information Criteria

Akaike (AIC)	48383.783
Bayesian (BIC)	49068.607
Sample-Size Adjusted BIC (n* = (n + 2) / 24)	48652.472

Chi-Square Test of Model Fit

Value	545.102
Degrees of Freedom	220
P-Value	0.0000

Chi-Square Contribution From Each Group

NCNPF	151.976
CANPS	97.935
OTHER	295.191

RMSEA (Root Mean Square Error Of Approximation)

Estimate	0.057	
90 Percent C.I.	0.051	0.063
Probability RMSEA <= .05	0.032	

CFI/TLI

CFI	0.982
TLI	0.978

Chi-Square Test of Model Fit for the Baseline Model

Value	18360.833
Degrees of Freedom	273
P-Value	0.0000

SRMR (Standardized Root Mean Square Residual)

Value	0.033

MODEL RESULTS

	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
Group NCNPF				
DNORMS BY				
X9	1.000	0.000	999.000	999.000
X10	1.065	0.022	48.719	0.000
INORMS BY				
X6	1.000	0.000	999.000	999.000
X7	1.099	0.022	50.354	0.000
X8	0.938	0.021	44.733	0.000
EFFS BY				
X1	1.000	0.000	999.000	999.000
X3	1.040	0.017	61.009	0.000
X5	1.008	0.018	55.593	0.000
EFFC BY				
X2	1.000	0.000	999.000	999.000
X4	0.998	0.009	111.505	0.000
PEBG BY				
PEB	1.000	0.000	999.000	999.000
PEBP	0.537	0.136	3.949	0.000
EFFS ON				
DNORMS	-0.076	0.258	-0.293	0.769
INORMS	0.575	0.262	2.197	0.028
EFFC ON				
EFFS	1.021	0.032	31.591	0.000
PEBG ON				
EFFS	0.041	0.327	0.126	0.900
EFFC	0.065	0.295	0.222	0.825
INORMS	0.369	0.349	1.056	0.291
DNORMS	-0.271	0.335	-0.808	0.419
DNORMS ON				
ENGAGE	0.026	0.008	3.357	0.001
INORMS ON				
ENGAGE	0.025	0.008	3.215	0.001
EFFS ON				
ENGAGE	0.022	0.006	3.836	0.000
EFFC ON				
ENGAGE	-0.004	0.003	-1.141	0.254
PEBG ON				
ENGAGE	0.018	0.008	2.319	0.020
AGE	0.003	0.002	1.205	0.228
ENGAGE ON				
AGE	0.017	0.020	0.873	0.383

INORMS WITH				
DNORMS	1.008	0.092	10.973	0.000
Intercepts				
ENGAGE	9.183	0.951	9.661	0.000
PEB	4.133	0.131	31.521	0.000
PEBP	0.438	0.097	4.531	0.000
X1	3.117	0.084	37.064	0.000
X2	3.224	0.087	37.048	0.000
X3	3.095	0.087	35.731	0.000
X4	3.229	0.087	37.249	0.000
X5	3.090	0.084	36.713	0.000
X6	2.758	0.099	27.906	0.000
X7	2.891	0.109	26.619	0.000
X8	2.385	0.093	25.632	0.000
X9	2.560	0.102	25.146	0.000
X10	2.612	0.108	24.111	0.000
DNORMS	0.000	0.000	999.000	999.000
INORMS	0.000	0.000	999.000	999.000
EFFS	0.000	0.000	999.000	999.000
EFFC	0.000	0.000	999.000	999.000
PEBG	0.000	0.000	999.000	999.000
Residual Variances				
ENGAGE	66.558	5.499	12.104	0.000
PEB	0.887	0.295	3.003	0.003
PEBP	6.939	0.579	11.975	0.000
X1	0.323	0.030	10.697	0.000
X2	0.071	0.010	7.217	0.000
X3	0.136	0.016	8.488	0.000
X4	0.038	0.008	4.502	0.000
X5	0.167	0.018	9.408	0.000
X6	0.286	0.032	9.018	0.000
X7	0.319	0.036	8.875	0.000
X8	0.294	0.031	9.645	0.000
X9	0.293	0.035	8.417	0.000
X10	0.266	0.036	7.425	0.000
DNORMS	1.076	0.103	10.422	0.000
INORMS	1.040	0.097	10.676	0.000
EFFS	0.495	0.050	9.995	0.000
EFFC	0.079	0.014	5.546	0.000
PEBG	0.072	0.285	0.252	0.801
Group CANPS				
DNORMS BY				
X9	1.000	0.000	999.000	999.000
X10	1.065	0.022	48.719	0.000
INORMS BY				
X6	1.000	0.000	999.000	999.000
X7	1.099	0.022	50.354	0.000
X8	0.938	0.021	44.733	0.000
EFFS BY				
X1	1.000	0.000	999.000	999.000
X3	1.040	0.017	61.009	0.000
X5	1.008	0.018	55.593	0.000
EFFC BY				
X2	1.000	0.000	999.000	999.000
X4	0.998	0.009	111.505	0.000

PEBG BY				
PEB	1.000	0.000	999.000	999.000
PEBP	0.537	0.136	3.949	0.000
EFFS ON				
DNORMS	0.184	0.291	0.634	0.526
INORMS	0.402	0.287	1.400	0.161
EFFC ON				
EFFS	1.037	0.032	32.892	0.000
PEBG ON				
EFFS	-0.449	0.507	-0.885	0.376
EFFC	0.612	0.473	1.294	0.196
INORMS	0.239	0.273	0.877	0.381
DNORMS	0.034	0.274	0.122	0.903
DNORMS ON				
ENGAGE	0.033	0.010	3.415	0.001
INORMS ON				
ENGAGE	0.028	0.010	2.956	0.003
EFFS ON				
ENGAGE	0.011	0.007	1.539	0.124
EFFC ON				
ENGAGE	-0.002	0.003	-0.802	0.423
PEBG ON				
ENGAGE	0.007	0.007	0.992	0.321
AGE	0.000	0.002	0.199	0.842
ENGAGE ON				
AGE	0.004	0.028	0.140	0.889
INORMS WITH				
DNORMS	1.244	0.148	8.400	0.000
Intercepts				
ENGAGE	10.806	1.391	7.766	0.000
PEB	4.133	0.131	31.521	0.000
PEBP	0.438	0.097	4.531	0.000
X1	3.117	0.084	37.064	0.000
X2	3.224	0.087	37.048	0.000
X3	3.095	0.087	35.731	0.000
X4	3.229	0.087	37.249	0.000
X5	3.090	0.084	36.713	0.000
X6	2.758	0.099	27.906	0.000
X7	2.891	0.109	26.619	0.000
X8	2.385	0.093	25.632	0.000
X9	2.560	0.102	25.146	0.000
X10	2.612	0.108	24.111	0.000
DNORMS	0.226	0.172	1.313	0.189
INORMS	0.231	0.171	1.352	0.176
EFFS	-0.198	0.123	-1.605	0.108
EFFC	-0.056	0.057	-0.983	0.326
PEBG	0.063	0.196	0.321	0.749
Residual Variances				
ENGAGE	94.557	10.348	9.138	0.000
PEB	0.973	0.150	6.467	0.000

PEBP	0.507	0.064	7.980	0.000
X1	0.405	0.048	8.504	0.000
X2	0.077	0.013	5.992	0.000
X3	0.082	0.015	5.325	0.000
X4	0.049	0.011	4.398	0.000
X5	0.166	0.022	7.493	0.000
X6	0.221	0.038	5.746	0.000
X7	0.323	0.051	6.347	0.000
X8	0.581	0.072	8.056	0.000
X9	0.371	0.054	6.876	0.000
X10	0.212	0.047	4.552	0.000
DNORMS	1.303	0.161	8.103	0.000
INORMS	1.325	0.159	8.345	0.000
EFFS	0.670	0.082	8.170	0.000
EFFC	0.049	0.015	3.164	0.002
PEBG	-0.008	0.104	-0.074	0.941

Group OTHER

DNORMS BY				
X9	1.000	0.000	999.000	999.000
X10	1.065	0.022	48.719	0.000
INORMS BY				
X6	1.000	0.000	999.000	999.000
X7	1.099	0.022	50.354	0.000
X8	0.938	0.021	44.733	0.000
EFFS BY				
X1	1.000	0.000	999.000	999.000
X3	1.040	0.017	61.009	0.000
X5	1.008	0.018	55.593	0.000
EFFC BY				
X2	1.000	0.000	999.000	999.000
X4	0.998	0.009	111.505	0.000
PEBG BY				
PEB	1.000	0.000	999.000	999.000
PEBP	0.537	0.136	3.949	0.000
EFFS ON				
DNORMS	-0.244	0.192	-1.270	0.204
INORMS	0.946	0.198	4.766	0.000
EFFC ON				
EFFS	1.035	0.018	57.054	0.000
PEBG ON				
EFFS	0.748	0.360	2.076	0.038
EFFC	-0.463	0.333	-1.392	0.164
INORMS	-0.136	0.248	-0.550	0.582
DNORMS	0.345	0.226	1.525	0.127
DNORMS ON				
ENGAGE	0.028	0.004	7.688	0.000
INORMS ON				
ENGAGE	0.031	0.003	8.883	0.000
EFFS ON				
ENGAGE	0.012	0.003	4.322	0.000

EFFC ON				
ENGAGE	0.000	0.001	0.223	0.824
PEBG ON				
ENGAGE	0.004	0.003	1.091	0.275
AGE	0.001	0.001	0.648	0.517
ENGAGE ON				
AGE	-0.006	0.015	-0.396	0.692
INORMS WITH				
DNORMS	1.126	0.060	18.734	0.000
Intercepts				
ENGAGE	12.033	0.712	16.904	0.000
PEB	4.133	0.131	31.521	0.000
PEBP	0.438	0.097	4.531	0.000
X1	3.117	0.084	37.064	0.000
X2	3.224	0.087	37.048	0.000
X3	3.095	0.087	35.731	0.000
X4	3.229	0.087	37.249	0.000
X5	3.090	0.084	36.713	0.000
X6	2.758	0.099	27.906	0.000
X7	2.891	0.109	26.619	0.000
X8	2.385	0.093	25.632	0.000
X9	2.560	0.102	25.146	0.000
X10	2.612	0.108	24.111	0.000
DNORMS	0.074	0.116	0.640	0.522
INORMS	0.012	0.112	0.109	0.913
EFFS	-0.080	0.087	-0.916	0.360
EFFC	-0.130	0.042	-3.140	0.002
PEBG	0.099	0.161	0.614	0.539
Residual Variances				
ENGAGE	115.835	5.410	21.413	0.000
PEB	0.785	0.276	2.848	0.004
PEBP	19.622	0.922	21.292	0.000
X1	0.263	0.014	18.730	0.000
X2	0.072	0.005	13.059	0.000
X3	0.129	0.008	15.663	0.000
X4	0.059	0.005	11.494	0.000
X5	0.217	0.012	18.139	0.000
X6	0.357	0.022	16.312	0.000
X7	0.314	0.021	14.769	0.000
X8	0.426	0.024	17.781	0.000
X9	0.377	0.024	15.391	0.000
X10	0.323	0.024	13.246	0.000
DNORMS	1.205	0.070	17.196	0.000
INORMS	1.137	0.065	17.566	0.000
EFFS	0.504	0.033	15.169	0.000
EFFC	0.037	0.007	5.635	0.000
PEBG	0.162	0.274	0.590	0.555

QUALITY OF NUMERICAL RESULTS

Condition Number for the Information Matrix 0.844E-06
(ratio of smallest to largest eigenvalue)

STANDARDIZED MODEL RESULTS

STDYX Standardization

	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
Group NCNPF				
DNORMS BY				
X9	0.891	0.015	60.814	0.000
X10	0.909	0.014	67.143	0.000
INORMS BY				
X6	0.889	0.014	63.775	0.000
X7	0.896	0.013	68.114	0.000
X8	0.874	0.015	58.863	0.000
EFFS BY				
X1	0.849	0.016	53.925	0.000
X3	0.932	0.009	100.070	0.000
X5	0.914	0.011	86.009	0.000
EFFC BY				
X2	0.964	0.006	173.781	0.000
X4	0.980	0.005	208.189	0.000
PEBG BY				
PEB	0.384	0.359	1.071	0.284
PEBP	0.080	0.075	1.057	0.291
EFFS ON				
DNORMS	-0.088	0.299	-0.293	0.769
INORMS	0.655	0.295	2.216	0.027
EFFC ON				
EFFS	0.965	0.012	82.007	0.000
PEBG ON				
EFFS	0.096	0.771	0.124	0.901
EFFC	0.161	0.737	0.218	0.827
INORMS	0.978	1.248	0.784	0.433
DNORMS	-0.732	1.086	-0.674	0.500
DNORMS ON				
ENGAGE	0.204	0.059	3.429	0.001
INORMS ON				
ENGAGE	0.193	0.059	3.278	0.001
EFFS ON				
ENGAGE	0.193	0.050	3.874	0.000
EFFC ON				
ENGAGE	-0.030	0.026	-1.139	0.255
PEBG ON				
ENGAGE	0.367	0.357	1.029	0.304
AGE	0.175	0.222	0.792	0.429
ENGAGE ON				
AGE	0.051	0.058	0.874	0.382
INORMS WITH				
DNORMS	0.953	0.014	66.648	0.000

Intercepts				
ENGAGE	1.124	0.128	8.787	0.000
PEB	4.052	0.229	17.734	0.000
PEBP	0.166	0.037	4.435	0.000
X1	2.898	0.145	19.933	0.000
X2	3.219	0.174	18.525	0.000
X3	3.037	0.166	18.310	0.000
X4	3.284	0.180	18.291	0.000
X5	3.069	0.163	18.774	0.000
X6	2.360	0.135	17.504	0.000
X7	2.268	0.133	17.098	0.000
X8	2.137	0.126	16.899	0.000
X9	2.153	0.132	16.331	0.000
X10	2.105	0.132	15.990	0.000
DNORMS	0.000	0.000	999.000	999.000
INORMS	0.000	0.000	999.000	999.000
EFFS	0.000	0.000	999.000	999.000
EFFC	0.000	0.000	999.000	999.000
PEBG	0.000	0.000	999.000	999.000
Residual Variances				
ENGAGE	0.997	0.006	168.103	0.000
PEB	0.852	0.276	3.094	0.002
PEBP	0.994	0.012	82.714	0.000
X1	0.279	0.027	10.451	0.000
X2	0.071	0.011	6.618	0.000
X3	0.131	0.017	7.557	0.000
X4	0.040	0.009	4.289	0.000
X5	0.165	0.019	8.485	0.000
X6	0.209	0.025	8.447	0.000
X7	0.196	0.024	8.327	0.000
X8	0.236	0.026	9.108	0.000
X9	0.207	0.026	7.936	0.000
X10	0.173	0.025	7.023	0.000
DNORMS	0.959	0.024	39.671	0.000
INORMS	0.963	0.023	42.403	0.000
EFFS	0.594	0.050	11.923	0.000
EFFC	0.084	0.016	5.172	0.000
PEBG	0.468	0.995	0.471	0.638
Group CANPS				
DNORMS BY				
X9	0.889	0.018	49.854	0.000
X10	0.939	0.015	64.233	0.000
INORMS BY				
X6	0.929	0.014	67.054	0.000
X7	0.916	0.015	62.808	0.000
X8	0.824	0.023	35.192	0.000
EFFS BY				
X1	0.864	0.018	47.601	0.000
X3	0.970	0.007	149.165	0.000
X5	0.938	0.010	93.013	0.000
EFFC BY				
X2	0.972	0.005	177.707	0.000
X4	0.982	0.004	218.946	0.000
PEBG BY				
PEB	0.457	0.115	3.962	0.000

PEBP	0.357	0.094	3.806	0.000
EFFS ON				
DNORMS	0.200	0.315	0.635	0.525
INORMS	0.436	0.310	1.408	0.159
EFFC ON				
EFFS	0.986	0.009	106.078	0.000
PEBG ON				
EFFS	-0.966	1.107	-0.873	0.383
EFFC	1.385	1.090	1.271	0.204
INORMS	0.559	0.648	0.863	0.388
DNORMS	0.078	0.641	0.122	0.903
DNORMS ON				
ENGAGE	0.267	0.075	3.547	0.000
INORMS ON				
ENGAGE	0.231	0.076	3.040	0.002
EFFS ON				
ENGAGE	0.099	0.064	1.542	0.123
EFFC ON				
ENGAGE	-0.020	0.025	-0.800	0.424
PEBG ON				
ENGAGE	0.135	0.135	1.002	0.316
AGE	0.025	0.123	0.200	0.842
ENGAGE ON				
AGE	0.011	0.077	0.140	0.889
INORMS WITH				
DNORMS	0.946	0.017	54.165	0.000
Intercepts				
ENGAGE	1.111	0.156	7.115	0.000
PEB	3.727	0.235	15.880	0.000
PEBP	0.575	0.133	4.311	0.000
X1	2.469	0.133	18.604	0.000
X2	2.731	0.163	16.740	0.000
X3	2.645	0.160	16.497	0.000
X4	2.769	0.167	16.544	0.000
X5	2.635	0.153	17.191	0.000
X6	2.167	0.137	15.811	0.000
X7	2.036	0.130	15.603	0.000
X8	1.771	0.107	16.577	0.000
X9	1.922	0.124	15.529	0.000
X10	1.945	0.132	14.776	0.000
DNORMS	0.191	0.148	1.288	0.198
INORMS	0.195	0.147	1.328	0.184
EFFS	-0.182	0.111	-1.633	0.102
EFFC	-0.048	0.049	-0.983	0.326
PEBG	0.124	0.392	0.316	0.752
Residual Variances				
ENGAGE	1.000	0.002	597.553	0.000
PEB	0.791	0.105	7.506	0.000
PEBP	0.873	0.067	13.028	0.000
X1	0.254	0.031	8.093	0.000
X2	0.055	0.011	5.219	0.000

X3	0.060	0.013	4.728	0.000
X4	0.036	0.009	4.059	0.000
X5	0.121	0.019	6.396	0.000
X6	0.136	0.026	5.285	0.000
X7	0.160	0.027	5.992	0.000
X8	0.320	0.039	8.299	0.000
X9	0.209	0.032	6.590	0.000
X10	0.118	0.027	4.282	0.000
DNORMS	0.929	0.040	23.127	0.000
INORMS	0.947	0.035	26.914	0.000
EFFS	0.564	0.061	9.236	0.000
EFFC	0.037	0.012	3.020	0.003
PEBG	-0.030	999.000	999.000	999.000

Group OTHER

DNORMS BY				
X9	0.880	0.009	95.803	0.000
X10	0.905	0.008	110.737	0.000
INORMS BY				
X6	0.882	0.009	102.993	0.000
X7	0.910	0.007	126.408	0.000
X8	0.849	0.010	84.170	0.000
EFFS BY				
X1	0.906	0.006	143.194	0.000
X3	0.954	0.004	267.832	0.000
X5	0.922	0.005	170.525	0.000
EFFC BY				
X2	0.974	0.002	423.178	0.000
X4	0.978	0.002	463.111	0.000
PEBG BY				
PEB	0.594	0.190	3.130	0.002
PEBP	0.079	0.029	2.684	0.007
EFFS ON				
DNORMS	-0.252	0.198	-1.272	0.203
INORMS	0.961	0.198	4.844	0.000
EFFC ON				
EFFS	0.985	0.005	210.155	0.000
PEBG ON				
EFFS	1.256	0.728	1.726	0.084
EFFC	-0.817	0.644	-1.268	0.205
INORMS	-0.233	0.431	-0.540	0.590
DNORMS	0.600	0.441	1.361	0.174
DNORMS ON				
ENGAGE	0.262	0.033	8.001	0.000
INORMS ON				
ENGAGE	0.296	0.032	9.361	0.000
EFFS ON				
ENGAGE	0.116	0.027	4.327	0.000
EFFC ON				
ENGAGE	0.002	0.011	0.223	0.824

PEBG ON				
ENGAGE	0.060	0.058	1.023	0.306
AGE	0.032	0.051	0.637	0.524
ENGAGE ON				
AGE	-0.013	0.033	-0.396	0.692
INORMS WITH				
DNORMS	0.962	0.008	117.077	0.000
Intercepts				
ENGAGE	1.118	0.071	15.811	0.000
PEB	3.753	0.148	25.380	0.000
PEBP	0.099	0.022	4.493	0.000
X1	2.569	0.091	28.092	0.000
X2	2.720	0.097	28.064	0.000
X3	2.582	0.094	27.494	0.000
X4	2.742	0.097	28.156	0.000
X5	2.570	0.092	28.044	0.000
X6	2.178	0.093	23.497	0.000
X7	2.142	0.095	22.612	0.000
X8	1.933	0.087	22.097	0.000
X9	1.981	0.091	21.796	0.000
X10	1.952	0.093	20.974	0.000
DNORMS	0.065	0.102	0.638	0.523
INORMS	0.011	0.101	0.109	0.913
EFFS	-0.073	0.079	-0.918	0.359
EFFC	-0.113	0.036	-3.136	0.002
PEBG	0.151	0.251	0.600	0.548
Residual Variances				
ENGAGE	1.000	0.001	1156.818	0.000
PEB	0.647	0.226	2.869	0.004
PEBP	0.994	0.005	213.017	0.000
X1	0.179	0.011	15.581	0.000
X2	0.051	0.004	11.388	0.000
X3	0.090	0.007	13.219	0.000
X4	0.043	0.004	10.292	0.000
X5	0.150	0.010	15.090	0.000
X6	0.223	0.015	14.747	0.000
X7	0.173	0.013	13.188	0.000
X8	0.280	0.017	16.336	0.000
X9	0.226	0.016	13.952	0.000
X10	0.180	0.015	12.185	0.000
DNORMS	0.931	0.017	54.139	0.000
INORMS	0.912	0.019	48.666	0.000
EFFS	0.417	0.026	15.994	0.000
EFFC	0.028	0.005	5.488	0.000
PEBG	0.377	0.402	0.939	0.348

STDY Standardization

	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
Group NCNPF				
DNORMS BY				
X9	0.891	0.015	60.814	0.000
X10	0.909	0.014	67.143	0.000
INORMS BY				

X6	0.889	0.014	63.775	0.000
X7	0.896	0.013	68.114	0.000
X8	0.874	0.015	58.863	0.000
EFFS BY				
X1	0.849	0.016	53.925	0.000
X3	0.932	0.009	100.070	0.000
X5	0.914	0.011	86.009	0.000
EFFC BY				
X2	0.964	0.006	173.781	0.000
X4	0.980	0.005	208.189	0.000
PEBG BY				
PEB	0.384	0.359	1.071	0.284
PEBP	0.080	0.075	1.057	0.291
EFFS ON				
DNORMS	-0.088	0.299	-0.293	0.769
INORMS	0.655	0.295	2.216	0.027
EFFC ON				
EFFS	0.965	0.012	82.007	0.000
PEBG ON				
EFFS	0.096	0.771	0.124	0.901
EFFC	0.161	0.737	0.218	0.827
INORMS	0.978	1.248	0.784	0.433
DNORMS	-0.732	1.086	-0.674	0.500
DNORMS ON				
ENGAGE	0.204	0.059	3.429	0.001
INORMS ON				
ENGAGE	0.193	0.059	3.278	0.001
EFFS ON				
ENGAGE	0.193	0.050	3.874	0.000
EFFC ON				
ENGAGE	-0.030	0.026	-1.139	0.255
PEBG ON				
ENGAGE	0.367	0.357	1.029	0.304
AGE	0.007	0.009	0.792	0.428
ENGAGE ON				
AGE	0.002	0.002	0.874	0.382
INORMS WITH				
DNORMS	0.953	0.014	66.648	0.000
Intercepts				
ENGAGE	1.124	0.128	8.787	0.000
PEB	4.052	0.229	17.734	0.000
PEBP	0.166	0.037	4.435	0.000
X1	2.898	0.145	19.933	0.000
X2	3.219	0.174	18.525	0.000
X3	3.037	0.166	18.310	0.000
X4	3.284	0.180	18.291	0.000
X5	3.069	0.163	18.774	0.000
X6	2.360	0.135	17.504	0.000
X7	2.268	0.133	17.098	0.000

X8	2.137	0.126	16.899	0.000
X9	2.153	0.132	16.331	0.000
X10	2.105	0.132	15.990	0.000
DNORMS	0.000	0.000	999.000	999.000
INORMS	0.000	0.000	999.000	999.000
EFFS	0.000	0.000	999.000	999.000
EFFC	0.000	0.000	999.000	999.000
PEBG	0.000	0.000	999.000	999.000

Residual Variances

ENGAGE	0.997	0.006	168.103	0.000
PEB	0.852	0.276	3.094	0.002
PEBP	0.994	0.012	82.714	0.000
X1	0.279	0.027	10.451	0.000
X2	0.071	0.011	6.618	0.000
X3	0.131	0.017	7.557	0.000
X4	0.040	0.009	4.289	0.000
X5	0.165	0.019	8.485	0.000
X6	0.209	0.025	8.447	0.000
X7	0.196	0.024	8.327	0.000
X8	0.236	0.026	9.108	0.000
X9	0.207	0.026	7.936	0.000
X10	0.173	0.025	7.023	0.000
DNORMS	0.959	0.024	39.671	0.000
INORMS	0.963	0.023	42.403	0.000
EFFS	0.594	0.050	11.923	0.000
EFFC	0.084	0.016	5.172	0.000
PEBG	0.468	0.995	0.471	0.638

Group CANPS

DNORMS BY

X9	0.889	0.018	49.854	0.000
X10	0.939	0.015	64.233	0.000

INORMS BY

X6	0.929	0.014	67.054	0.000
X7	0.916	0.015	62.808	0.000
X8	0.824	0.023	35.192	0.000

EFFS BY

X1	0.864	0.018	47.601	0.000
X3	0.970	0.007	149.165	0.000
X5	0.938	0.010	93.013	0.000

EFFC BY

X2	0.972	0.005	177.707	0.000
X4	0.982	0.004	218.946	0.000

PEBG BY

PEB	0.457	0.115	3.962	0.000
PEBP	0.357	0.094	3.806	0.000

EFFS ON

DNORMS	0.200	0.315	0.635	0.525
INORMS	0.436	0.310	1.408	0.159

EFFC ON

EFFS	0.986	0.009	106.078	0.000

PEBG ON

EFFS	-0.966	1.107	-0.873	0.383
EFFC	1.385	1.090	1.271	0.204

INORMS	0.559	0.648	0.863	0.388
DNORMS	0.078	0.641	0.122	0.903
DNORMS ON				
ENGAGE	0.267	0.075	3.547	0.000
INORMS ON				
ENGAGE	0.231	0.076	3.040	0.002
EFFS ON				
ENGAGE	0.099	0.064	1.542	0.123
EFFC ON				
ENGAGE	-0.020	0.025	-0.800	0.424
PEBG ON				
ENGAGE	0.135	0.135	1.002	0.316
AGE	0.001	0.005	0.200	0.842
ENGAGE ON				
AGE	0.000	0.003	0.140	0.889
INORMS WITH				
DNORMS	0.946	0.017	54.165	0.000
Intercepts				
ENGAGE	1.111	0.156	7.115	0.000
PEB	3.727	0.235	15.880	0.000
PEBP	0.575	0.133	4.311	0.000
X1	2.469	0.133	18.604	0.000
X2	2.731	0.163	16.740	0.000
X3	2.645	0.160	16.497	0.000
X4	2.769	0.167	16.544	0.000
X5	2.635	0.153	17.191	0.000
X6	2.167	0.137	15.811	0.000
X7	2.036	0.130	15.603	0.000
X8	1.771	0.107	16.577	0.000
X9	1.922	0.124	15.529	0.000
X10	1.945	0.132	14.776	0.000
DNORMS	0.191	0.148	1.288	0.198
INORMS	0.195	0.147	1.328	0.184
EFFS	-0.182	0.111	-1.633	0.102
EFFC	-0.048	0.049	-0.983	0.326
PEBG	0.124	0.392	0.316	0.752
Residual Variances				
ENGAGE	1.000	0.002	597.553	0.000
PEB	0.791	0.105	7.506	0.000
PEBP	0.873	0.067	13.028	0.000
X1	0.254	0.031	8.093	0.000
X2	0.055	0.011	5.219	0.000
X3	0.060	0.013	4.728	0.000
X4	0.036	0.009	4.059	0.000
X5	0.121	0.019	6.396	0.000
X6	0.136	0.026	5.285	0.000
X7	0.160	0.027	5.992	0.000
X8	0.320	0.039	8.299	0.000
X9	0.209	0.032	6.590	0.000
X10	0.118	0.027	4.282	0.000
DNORMS	0.929	0.040	23.127	0.000
INORMS	0.947	0.035	26.914	0.000
EFFS	0.564	0.061	9.236	0.000
EFFC	0.037	0.012	3.020	0.003

PEBG	999.000	999.000	999.000	999.000

Group OTHER

DNORMS BY				
X9	0.880	0.009	95.803	0.000
X10	0.905	0.008	110.737	0.000
INORMS BY				
X6	0.882	0.009	102.993	0.000
X7	0.910	0.007	126.408	0.000
X8	0.849	0.010	84.170	0.000
EFFS BY				
X1	0.906	0.006	143.194	0.000
X3	0.954	0.004	267.832	0.000
X5	0.922	0.005	170.525	0.000
EFFC BY				
X2	0.974	0.002	423.178	0.000
X4	0.978	0.002	463.111	0.000
PEBG BY				
PEB	0.594	0.190	3.130	0.002
PEBP	0.079	0.029	2.684	0.007
EFFS ON				
DNORMS	-0.252	0.198	-1.272	0.203
INORMS	0.961	0.198	4.844	0.000
EFFC ON				
EFFS	0.985	0.005	210.155	0.000
PEBG ON				
EFFS	1.256	0.728	1.726	0.084
EFFC	-0.817	0.644	-1.268	0.205
INORMS	-0.233	0.431	-0.540	0.590
DNORMS	0.600	0.441	1.361	0.174
DNORMS ON				
ENGAGE	0.262	0.033	8.001	0.000
INORMS ON				
ENGAGE	0.296	0.032	9.361	0.000
EFFS ON				
ENGAGE	0.116	0.027	4.327	0.000
EFFC ON				
ENGAGE	0.002	0.011	0.223	0.824
PEBG ON				
ENGAGE	0.060	0.058	1.023	0.306
AGE	0.001	0.002	0.637	0.524
ENGAGE ON				
AGE	-0.001	0.001	-0.396	0.692
INORMS WITH				
DNORMS	0.962	0.008	117.077	0.000
Intercepts				
ENGAGE	1.118	0.071	15.811	0.000

PEB	3.753	0.148	25.380	0.000
PEBP	0.099	0.022	4.493	0.000
X1	2.569	0.091	28.092	0.000
X2	2.720	0.097	28.064	0.000
X3	2.582	0.094	27.494	0.000
X4	2.742	0.097	28.156	0.000
X5	2.570	0.092	28.044	0.000
X6	2.178	0.093	23.497	0.000
X7	2.142	0.095	22.612	0.000
X8	1.933	0.087	22.097	0.000
X9	1.981	0.091	21.796	0.000
X10	1.952	0.093	20.974	0.000
DNORMS	0.065	0.102	0.638	0.523
INORMS	0.011	0.101	0.109	0.913
EFFS	-0.073	0.079	-0.918	0.359
EFFC	-0.113	0.036	-3.136	0.002
PEBG	0.151	0.251	0.600	0.548

Residual Variances

ENGAGE	1.000	0.001	1156.818	0.000
PEB	0.647	0.226	2.869	0.004
PEBP	0.994	0.005	213.017	0.000
X1	0.179	0.011	15.581	0.000
X2	0.051	0.004	11.388	0.000
X3	0.090	0.007	13.219	0.000
X4	0.043	0.004	10.292	0.000
X5	0.150	0.010	15.090	0.000
X6	0.223	0.015	14.747	0.000
X7	0.173	0.013	13.188	0.000
X8	0.280	0.017	16.336	0.000
X9	0.226	0.016	13.952	0.000
X10	0.180	0.015	12.185	0.000
DNORMS	0.931	0.017	54.139	0.000
INORMS	0.912	0.019	48.666	0.000
EFFS	0.417	0.026	15.994	0.000
EFFC	0.028	0.005	5.488	0.000
PEBG	0.377	0.402	0.939	0.348

STD Standardization

	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
Group NCNPF				
DNORMS BY				
X9	1.059	0.051	20.953	0.000
X10	1.128	0.053	21.156	0.000
INORMS BY				
X6	1.039	0.049	21.419	0.000
X7	1.143	0.053	21.531	0.000
X8	0.975	0.046	21.168	0.000
EFFS BY				
X1	0.913	0.042	21.714	0.000
X3	0.950	0.043	22.317	0.000
X5	0.920	0.042	22.166	0.000
EFFC BY				
X2	0.966	0.041	23.352	0.000
X4	0.964	0.041	23.468	0.000

PEBG BY				
PEB	0.392	0.366	1.070	0.285
PEBP	0.211	0.199	1.056	0.291
EFFS ON				
DNORMS	-0.088	0.299	-0.293	0.769
INORMS	0.655	0.295	2.216	0.027
EFFC ON				
EFFS	0.965	0.012	82.007	0.000
PEBG ON				
EFFS	0.096	0.771	0.124	0.901
EFFC	0.161	0.737	0.218	0.827
INORMS	0.978	1.248	0.784	0.433
DNORMS	-0.732	1.086	-0.674	0.500
DNORMS ON				
ENGAGE	0.025	0.007	3.461	0.001
INORMS ON				
ENGAGE	0.024	0.007	3.306	0.001
EFFS ON				
ENGAGE	0.024	0.006	3.915	0.000
EFFC ON				
ENGAGE	-0.004	0.003	-1.140	0.254
PEBG ON				
ENGAGE	0.045	0.044	1.029	0.303
AGE	0.007	0.009	0.792	0.428
ENGAGE ON				
AGE	0.017	0.020	0.873	0.383
INORMS WITH				
DNORMS	0.953	0.014	66.648	0.000
Intercepts				
ENGAGE	9.183	0.951	9.661	0.000
PEB	4.133	0.131	31.521	0.000
PEBP	0.438	0.097	4.531	0.000
X1	3.117	0.084	37.064	0.000
X2	3.224	0.087	37.048	0.000
X3	3.095	0.087	35.731	0.000
X4	3.229	0.087	37.249	0.000
X5	3.090	0.084	36.713	0.000
X6	2.758	0.099	27.906	0.000
X7	2.891	0.109	26.619	0.000
X8	2.385	0.093	25.632	0.000
X9	2.560	0.102	25.146	0.000
X10	2.612	0.108	24.111	0.000
DNORMS	0.000	0.000	999.000	999.000
INORMS	0.000	0.000	999.000	999.000
EFFS	0.000	0.000	999.000	999.000
EFFC	0.000	0.000	999.000	999.000
PEBG	0.000	0.000	999.000	999.000
Residual Variances				
ENGAGE	66.558	5.499	12.104	0.000
PEB	0.887	0.295	3.003	0.003

PEBP	6.939	0.579	11.975	0.000
X1	0.323	0.030	10.697	0.000
X2	0.071	0.010	7.217	0.000
X3	0.136	0.016	8.488	0.000
X4	0.038	0.008	4.502	0.000
X5	0.167	0.018	9.408	0.000
X6	0.286	0.032	9.018	0.000
X7	0.319	0.036	8.875	0.000
X8	0.294	0.031	9.645	0.000
X9	0.293	0.035	8.417	0.000
X10	0.266	0.036	7.425	0.000
DNORMS	0.959	0.024	39.671	0.000
INORMS	0.963	0.023	42.403	0.000
EFFS	0.594	0.050	11.923	0.000
EFFC	0.084	0.016	5.172	0.000
PEBG	0.468	0.995	0.471	0.638

Group CANPS

DNORMS BY				
X9	1.185	0.073	16.310	0.000
X10	1.262	0.076	16.523	0.000
INORMS BY				
X6	1.183	0.071	16.745	0.000
X7	1.301	0.078	16.728	0.000
X8	1.110	0.068	16.338	0.000
EFFS BY				
X1	1.091	0.064	17.094	0.000
X3	1.135	0.065	17.506	0.000
X5	1.099	0.063	17.320	0.000
EFFC BY				
X2	1.147	0.065	17.779	0.000
X4	1.145	0.064	17.831	0.000
PEBG BY				
PEB	0.507	0.136	3.731	0.000
PEBP	0.272	0.075	3.619	0.000
EFFS ON				
DNORMS	0.200	0.315	0.635	0.525
INORMS	0.436	0.310	1.408	0.159
EFFC ON				
EFFS	0.986	0.009	106.078	0.000
PEBG ON				
EFFS	-0.966	1.107	-0.873	0.383
EFFC	1.385	1.090	1.271	0.204
INORMS	0.559	0.648	0.863	0.388
DNORMS	0.078	0.641	0.122	0.903
DNORMS ON				
ENGAGE	0.027	0.008	3.605	0.000
INORMS ON				
ENGAGE	0.024	0.008	3.079	0.002
EFFS ON				
ENGAGE	0.010	0.007	1.547	0.122

EFFC ON				
ENGAGE	-0.002	0.003	-0.801	0.423
PEBG ON				
ENGAGE	0.014	0.014	1.003	0.316
AGE	0.001	0.005	0.200	0.842
ENGAGE ON				
AGE	0.004	0.028	0.140	0.889
INORMS WITH				
DNORMS	0.946	0.017	54.165	0.000
Intercepts				
ENGAGE	10.806	1.391	7.766	0.000
PEB	4.133	0.131	31.521	0.000
PEBP	0.438	0.097	4.531	0.000
X1	3.117	0.084	37.064	0.000
X2	3.224	0.087	37.048	0.000
X3	3.095	0.087	35.731	0.000
X4	3.229	0.087	37.249	0.000
X5	3.090	0.084	36.713	0.000
X6	2.758	0.099	27.906	0.000
X7	2.891	0.109	26.619	0.000
X8	2.385	0.093	25.632	0.000
X9	2.560	0.102	25.146	0.000
X10	2.612	0.108	24.111	0.000
DNORMS	0.191	0.148	1.288	0.198
INORMS	0.195	0.147	1.328	0.184
EFFS	-0.182	0.111	-1.633	0.102
EFFC	-0.048	0.049	-0.983	0.326
PEBG	0.124	0.392	0.316	0.752
Residual Variances				
ENGAGE	94.557	10.348	9.138	0.000
PEB	0.973	0.150	6.467	0.000
PEBP	0.507	0.064	7.980	0.000
X1	0.405	0.048	8.504	0.000
X2	0.077	0.013	5.992	0.000
X3	0.082	0.015	5.325	0.000
X4	0.049	0.011	4.398	0.000
X5	0.166	0.022	7.493	0.000
X6	0.221	0.038	5.746	0.000
X7	0.323	0.051	6.347	0.000
X8	0.581	0.072	8.056	0.000
X9	0.371	0.054	6.876	0.000
X10	0.212	0.047	4.552	0.000
DNORMS	0.929	0.040	23.127	0.000
INORMS	0.947	0.035	26.914	0.000
EFFS	0.564	0.061	9.236	0.000
EFFC	0.037	0.012	3.020	0.003
PEBG	999.000	999.000	999.000	999.000
Group OTHER				
DNORMS BY				
X9	1.138	0.033	34.617	0.000
X10	1.212	0.034	35.832	0.000
INORMS BY				
X6	1.116	0.032	35.329	0.000
X7	1.227	0.034	36.524	0.000
X8	1.047	0.031	33.679	0.000

EFFS BY				
X1	1.099	0.030	36.634	0.000
X3	1.144	0.029	39.530	0.000
X5	1.108	0.029	37.825	0.000
EFFC BY				
X2	1.155	0.028	40.948	0.000
X4	1.152	0.028	41.201	0.000
PEBG BY				
PEB	0.654	0.210	3.119	0.002
PEBP	0.352	0.131	2.684	0.007
EFFS ON				
DNORMS	-0.252	0.198	-1.272	0.203
INORMS	0.961	0.198	4.844	0.000
EFFC ON				
EFFS	0.985	0.005	210.155	0.000
PEBG ON				
EFFS	1.256	0.728	1.726	0.084
EFFC	-0.817	0.644	-1.268	0.205
INORMS	-0.233	0.431	-0.540	0.590
DNORMS	0.600	0.441	1.361	0.174
DNORMS ON				
ENGAGE	0.024	0.003	8.124	0.000
INORMS ON				
ENGAGE	0.028	0.003	9.551	0.000
EFFS ON				
ENGAGE	0.011	0.002	4.344	0.000
EFFC ON				
ENGAGE	0.000	0.001	0.223	0.824
PEBG ON				
ENGAGE	0.006	0.005	1.023	0.306
AGE	0.001	0.002	0.637	0.524
ENGAGE ON				
AGE	-0.006	0.015	-0.396	0.692
INORMS WITH				
DNORMS	0.962	0.008	117.077	0.000
Intercepts				
ENGAGE	12.033	0.712	16.904	0.000
PEB	4.133	0.131	31.521	0.000
PEBP	0.438	0.097	4.531	0.000
X1	3.117	0.084	37.064	0.000
X2	3.224	0.087	37.048	0.000
X3	3.095	0.087	35.731	0.000
X4	3.229	0.087	37.249	0.000
X5	3.090	0.084	36.713	0.000
X6	2.758	0.099	27.906	0.000
X7	2.891	0.109	26.619	0.000
X8	2.385	0.093	25.632	0.000
X9	2.560	0.102	25.146	0.000
X10	2.612	0.108	24.111	0.000

DNORMS	0.065	0.102	0.638	0.523
INORMS	0.011	0.101	0.109	0.913
EFFS	-0.073	0.079	-0.918	0.359
EFFC	-0.113	0.036	-3.136	0.002
PEBG	0.151	0.251	0.600	0.548

Residual Variances

ENGAGE	115.835	5.410	21.413	0.000
PEB	0.785	0.276	2.848	0.004
PEBP	19.622	0.922	21.292	0.000
X1	0.263	0.014	18.730	0.000
X2	0.072	0.005	13.059	0.000
X3	0.129	0.008	15.663	0.000
X4	0.059	0.005	11.494	0.000
X5	0.217	0.012	18.139	0.000
X6	0.357	0.022	16.312	0.000
X7	0.314	0.021	14.769	0.000
X8	0.426	0.024	17.781	0.000
X9	0.377	0.024	15.391	0.000
X10	0.323	0.024	13.246	0.000
DNORMS	0.931	0.017	54.139	0.000
INORMS	0.912	0.019	48.666	0.000
EFFS	0.417	0.026	15.994	0.000
EFFC	0.028	0.005	5.488	0.000
PEBG	0.377	0.402	0.939	0.348

R-SQUARE

Group NCNPF

Observed Variable	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
ENGAGE	0.003	0.006	0.437	0.662
PEB	0.148	0.276	0.536	0.592
PEBP	0.006	0.012	0.528	0.597
X1	0.721	0.027	26.963	0.000
X2	0.929	0.011	86.891	0.000
X3	0.869	0.017	50.035	0.000
X4	0.960	0.009	104.094	0.000
X5	0.835	0.019	43.005	0.000
X6	0.791	0.025	31.887	0.000
X7	0.804	0.024	34.057	0.000
X8	0.764	0.026	29.431	0.000
X9	0.793	0.026	30.407	0.000
X10	0.827	0.025	33.571	0.000

Latent Variable	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
DNORMS	0.041	0.024	1.714	0.086
INORMS	0.037	0.023	1.639	0.101
EFFS	0.406	0.050	8.142	0.000
EFFC	0.916	0.016	56.082	0.000
PEBG	0.532	0.995	0.534	0.593

Group CANPS

Observed Variable	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
ENGAGE	0.000	0.002	0.070	0.944

PEB	0.209	0.105	1.981	0.048
PEBP	0.127	0.067	1.903	0.057
X1	0.746	0.031	23.801	0.000
X2	0.945	0.011	88.854	0.000
X3	0.940	0.013	74.582	0.000
X4	0.964	0.009	109.473	0.000
X5	0.879	0.019	46.506	0.000
X6	0.864	0.026	33.527	0.000
X7	0.840	0.027	31.404	0.000
X8	0.680	0.039	17.596	0.000
X9	0.791	0.032	24.927	0.000
X10	0.882	0.027	32.116	0.000

Latent Variable	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
DNORMS	0.071	0.040	1.773	0.076
INORMS	0.053	0.035	1.520	0.128
EFFS	0.436	0.061	7.153	0.000
EFFC	0.963	0.012	78.036	0.000
PEBG	Undefined	0.10298E+01		

Group OTHER

Observed Variable	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
ENGAGE	0.000	0.001	0.198	0.843
PEB	0.353	0.226	1.565	0.118
PEBP	0.006	0.005	1.342	0.180
X1	0.821	0.011	71.597	0.000
X2	0.949	0.004	211.589	0.000
X3	0.910	0.007	133.916	0.000
X4	0.957	0.004	231.555	0.000
X5	0.850	0.010	85.262	0.000
X6	0.777	0.015	51.496	0.000
X7	0.827	0.013	63.204	0.000
X8	0.720	0.017	42.085	0.000
X9	0.774	0.016	47.901	0.000
X10	0.820	0.015	55.369	0.000

Latent Variable	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
DNORMS	0.069	0.017	4.000	0.000
INORMS	0.088	0.019	4.680	0.000
EFFS	0.583	0.026	22.343	0.000
EFFC	0.972	0.005	192.823	0.000
PEBG	0.623	0.402	1.550	0.121

MODEL MODIFICATION INDICES

NOTE: Modification indices for direct effects of observed dependent variables regressed on covariates may not be included. To include these, request MODINDICES (ALL).

Minimum M.I. value for printing the modification index 10.000

	M.I.	E.P.C.	Std E.P.C.	StdYX E.P.C.

Group NCNPF

WITH Statements

X9	WITH X6	11.313	0.083	0.083	0.286
X9	WITH X7	23.907	-0.130	-0.130	-0.424
X10	WITH X6	34.726	-0.147	-0.147	-0.532
X10	WITH X7	35.283	0.160	0.160	0.549
X9	WITH X7	13.631	-0.141	-0.141	-0.409
X10	WITH X7	18.495	0.154	0.154	0.589
X4	WITH X1	16.628	-0.026	-0.026	-0.205
X8	WITH X6	41.140	0.111	0.111	0.286
X8	WITH X7	12.727	-0.066	-0.066	-0.179
X9	WITH X6	21.933	0.080	0.080	0.218
X9	WITH X7	62.888	-0.139	-0.139	-0.404
X9	WITH X8	14.704	0.067	0.067	0.168
X10	WITH X6	84.433	-0.156	-0.156	-0.460
X10	WITH X7	159.230	0.222	0.222	0.696
X10	WITH X8	18.429	-0.075	-0.075	-0.201

DIAGRAM INFORMATION

Use View Diagram under the Diagram menu in the Mplus Editor to view the diagram. If running Mplus from the Mplus Diagrammer, the diagram opens automatically.

Diagram output
c:\users\serah\documents\research\dissertation\mplus data\peb2cgroups2.dgm

Beginning Time: 13:08:02
Ending Time:
13
:08:02
Elapsed Time:
0
0:00:00