EXPLAINING CONSERVATION BEHAVIORS TO REDUCE WILDLIFE CRIME: A CROSS-NATIONAL AND THEORETICAL COMPARISON

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ABSTRACT

Wildlife crimes such as poaching and the illegal trade in wild animals and plants are globally prolific and may converge with other serious crimes including drugs and arms trafficking. Wildlife crime is a wicked problem, requiring interdisciplinary approaches to manage its far-reaching impacts on the environment, social justice, public health, the economy, governance, etc. Conservation organizations frequently use public communication and campaigns to draw the public's attention to issues such as wildlife crime. These campaigns often urge audiences to take various actions such as donating money to support the organizations' efforts to combat wildlife crime. Despite their reliance on communication to reach and engage their audiences, little is publicly known about the effects of such communication on conservation behaviors. In fact, we do not yet know which social-psychological factors matter most in driving behaviors linked to curbing wildlife crime. This dissertation compares the theory of planned behavior and the value-belief-norm theory – both widely used to explain environmental behaviors – and compares responses from a cross-national group of participants from India and the United States of America to provide new empirical evidence of how well each theory performs in predicting intentions to donate money to conservation organizations to reduce wildlife crime. It also explores the potential for using wildlife value orientations in studies that focus specifically on wildlife-related behaviors, rather than the New Ecological Paradigm scale that is used as part of the value-belief-norm model. Data was collected from a total of 1,820 participants, of which 900 were from the U.S. and 920 were from India. The survey instrument assessed responses to the primary constructs in the planned behavior and value-belief-norm theory.

Data were analyzed using correlations, regressions, multi-group confirmatory factor analysis, and structural equation modeling.

Results indicate that the theory of planned behavior explained greater variance in donation intentions for both Indian and U.S. groups but attitude toward behavior did not have a significant association with intention in the multivariate analysis in either sample. While the value-belief-norm theory explained lesser variance in donation intentions, and it held up as expected for the U.S. sample with good reliability metrics, scale reliability was low for the Indian sample and convergent validity was poor overall with values and ecological worldview dimensions manifesting unexpectedly in multivariate regressions. Measurement models and structural models were different for both samples, necessitating a parallel analysis. A modified value-belief-norm model with mutualistic wildlife value orientations had slightly better fit for the India sample but slightly lower for the U.S. sample. Perceived behavioral control was the strongest predictor for India while personal norms mattered most in the US sample. Key contributions of this dissertation to advancing theory and building new empirical knowledge in environmental communication and conservation social science research are discussed. In recognizing that several existing scales were developed by and for primarily Western audiences, this dissertation also underscores the importance of cross-validating measures and being inclusive of communities in non-Western emerging economies. Theoretical and practical implications of the results along with directions for future research and limitations are also discussed.

With immense gratitude, I dedicate this dissertation to the people who, with their unwavering support, unconditional love, and fierce belief in me, have empowered me to accomplish this goal. To my village – my fiancé, soulmate, and best friend – Pushkar; my parents – Dr. Suvarna and Prasanna Joshi; my grandparents – Smt. Vasanti and Col. Vidyadhar Dixit; my OG queen – Ginny; my siblings – Parashar and Shruti; my parents-in-law – Pradnya and Pradeep Pandit; our sweet fur baby – Burfee; and my dearest friends – Rahul, Manmeeta, Meenal, Aakash, Suhita, Devashri, Paroma, and Kajal

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Right from his response to the cold email I sent when I was considering applying for the Information and Media PhD program at MSU, I have been incredibly fortunate to have an advisor and mentor as kind, empathetic, supportive, and open-minded as Dr. Bruno Takahashi. I cannot count the number of times over the last six years when I have silently thanked my stars that I get to work with an advisor who not only encourages me to pursue my passion and curiosity, but also offers support, advice, and opportunities for me to grow and has shown immense faith in me. Bruno has advocated for me, has encouraged me to pursue professional development opportunities, to explore and expand on my skills as a scholar and an educator, and he has been an unwavering pillar of support not only during "normal" times, but most importantly, during a pandemic that tore through so many of our lives. I don't know where I will be in 10 years, but I know that even then, I will cherish our equation and will do everything I can do remember and practice what Bruno has taught me about being a good advisor and a wonderful human being.

New to the world of theory, academic research, and to Michigan, I felt out of my depth for the entirety of my first year as PhD student. In one theory class, I was questioning my choice of pursuing a PhD because of how complex theory seemed and how difficult it was

for me to keep up with conversations. Then one afternoon, in the office of the professor teaching that class, I had my first "Aha!" moment. Dr. Serena Miller didn't have to, but she chose to spend hours talking to me till everything that had been evading my understanding till that point began to make perfect sense. With her unassuming, inclusive, empowering approach to mentorship, she sparked a lifelong curiosity and love for theory in my mind, and made me believe that I could, in fact, do this. Over the years, Dr. Miller has taken the initiative to coach me through some of the most important hurdles of being an academic and has consistently been one of the strongest allies for my peers and I in the program. I consider myself very fortunate to have learned so much from her, especially the high benchmark she sets for service to students, field, science, and society.

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journey. I do not know of a single person who is as selflessly caring as my fiancé, who has dealt with my stress, anxiety, and a whole lot more while bearing the larger burden for a substantial amount of time and has done so with dignity, love, and mind-boggling levels of resilience and ease, all while building up my spirits and helping me chase my dreams. I would simply not have been able to complete this PhD without his strength and faith, and without the empowered upbringing my parents gave me. On days when I found it difficult to get back up, they rallied around me and reminded me what I'm capable of. They have always led by example and inspired me to be better and do better. Being away from friends and family was already difficult without a pandemic thrown into the mix during which time I lived in perpetual fear of losing those closest to me, and in those moments I learned that even when faced with the harshest of adversities, I don't lose sight of what's most important to me and my never-give-up spirit was still intact. This PhD is a result of just that – not giving up. The love, faith, and support of my family and friends is and will always be the fuel that keeps me going.

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CHAPTER ONE: INTRODUCTION

Background

Across the world, wild animals and plants are traded every day – in-person and online – by sellers, intermediaries, buyers, fixers, etc. with an entire supply chain built to maintain the flow of live wildlife such as snakes, spiders, exotic birds, orchids, turtles, seahorses, etc. and parts or products made from wildlife such as elephant tusk ivory, rhino horn, pangolin scales, tiger or leopard skins, lion bones, mongoose hair, shark fins etc. (Kasper et al., 2020; Nijman et al., 2022). Wildlife or their parts and products are traded for various purposes; some people consume these parts or animals and plants as food; others believe that they hold medicinal properties and use them in traditional medicines; and there are also those who buy them as jewelry, fashion items, trophies or other kinds of status symbols, or to keep as pets (Anagnostou & Doberstein, 2022; UNODC, 2020). A substantial amount of this international trade, however, is illegal.

Crimes such as poaching (i.e., illegal hunting) and the trafficking or smuggling of wild animals, plants, and their parts or derivatives are often collectively referred to as the illegal wildlife trade (IWT) or as wildlife crimes (WLC). Globally, wildlife crimes are among the most lucrative and widespread criminal operations sometimes involving not only organized criminal syndicates, but now also known to frequently converge with other serious crimes such as the trafficking of drugs, weapons, and people, as well as crimes such as corruption, money laundering, fraud, murder, etc. (Anagnostou & Doberstein, 2022; Brashares et al., 2014; Dalpane & Baideldinova, 2022; Duffy & Brockington, 2022; Nellemann et al., 2014; UNODC, 2020).

Contrary to what the name suggests though, wildlife crimes do not merely have ecological impacts. While they certainly are one of the primary contributors of species extinction and biodiversity loss (O'Donoghue & Rutz, 2016), wildlife crimes also exacerbate issues of governance, law enforcement, policymaking, safeguarding human rights, conflict resolution, economic and social stability, animal welfare, environmental and social justice, and, as became evident during the SARS-CoV-2 (COVID-19) pandemic, they are very much also an issue of public health (Anagnostou & Doberstein, 2022; Bezerra-Santos et al., 2021; Brashares et al., 2014; Duffy & Brockington, 2022; Kahler & Gore, 2015; Nellemann et al., 2014; Wyatt et al., 2021; Zucca et al., 2020).

Due to the complex nature of the causes and consequences of wildlife crimes, they are considered 'wicked problems' – the kind of issues that are not "solved" but rather, must be studied and managed through holistic interdisciplinary approaches (Giannetta, 2017; Levin et al., 2012). Despite emerging interdisciplinary research on illegal wildlife trade and wildlife crimes from criminologists, economists, conservation biologists, and conservation social scientists (Bennett et al., 2017; Blair et al., 2017; Boratto & Gibbs, 2019), a communication-based perspective is markedly rare (Giannetta, 2017; Glenn et al., 2019; Kachen & Krishen, 2020). This is one of the knowledge gaps that this dissertation addresses.

A communication-based perspective is both necessary and important to the interdisciplinary study of wildlife crime because some of the most commonly deployed demand-reduction interventions to prevent and reduce wildlife crimes around the world are persuasive and strategic communication campaigns by conservation organizations, non-profits, and alliances. Conservation organizations use public communication and social marketing campaigns to draw the public's attention to wildlife crime and its impacts (Duthie et al., 2017; Greenfield & Veríssimo, 2019; Lundberg et al., 2019; Veríssimo, 2019; Veríssimo et al., 2017, 2018; Veríssimo & Wan, 2019). These campaigns may be aimed at educating or influencing audiences, often urging them to take various actions such as donating money to support the organizations' efforts to combat wildlife crime, or asking people to click on a web link to learn more about the issue or the organization's work to address it (Joshi et al., under review). Studying how wildlife crime is communicated and how that communication may influence emotional, cognitive, and behavioral responses among target audiences is an important way to assess the success of conservation campaigns, and to identify the salient factors that might explain, drive, or impede audience engagement. Currently, theories of environmental communication and environmental behavior have not been tested in the context of conservation behaviors associated with wildlife crime prevention. If conservation communication professionals and conservation social scientists want to understand what drives these behaviors, researchers will need to apply and test the predictive and explanatory powers of various theories to identify the predictors that matter most for different audience segments. This dissertation is a first step in that direction. Additionally, this dissertation helps meet the need for and underscores the value of publicly available, independent evaluations of the efficacy of such conservation communication campaigns (Khanwilkar et al., 2022; Veríssimo & Wan, 2019).

Many campaigns may aim to secure public donations for conservation organizations working on combating wildlife crime, among other issues. Considering that conservation organizations rely on public donations to support their programs, key questions need to be answered: 1) How is wildlife crime communicated as a problem? 2) Which social-psychological factors are salient influencers of conservation behaviors to reduce wildlife crime? 3) Through which mechanisms does wildlife crime-related communication influence behaviors to reduce wildlife crime?

While a previous study (Joshi et al., under review) partly answers the first question through a content analysis, this dissertation addresses some of these knowledge gaps by answering the second question using a survey, and it sets the stage for a follow-up study to answer the third question through an experiment.

This dissertation is based on a key finding from the previous study (Joshi et al., under review) that conservation organizations most frequently call for information-seeking and monetary donation behaviors in visual wildlife crime prevention ads. Despite valuable work on conservation social marketing and behavior change campaigns (Greenfield & Veríssimo, 2019; Veríssimo, 2019), communication scholars have rarely investigated how, for example, salient social-psychological factors may drive behaviors to reduce wildlife crime that audiences may adopt upon exposure to communication from conservation organizations (Giannetta, 2017).

Previous research largely suggests that environmental behaviors may be motivated by factors such as an individual's self-interest or intent to perform a behavior; their attitude toward the behavior; their values, beliefs, or norms, etc. (Bamberg & Möser, 2007; Kaiser et al., 2005; Kidd et al., 2019; Shreedhar & Mourato, 2018; Thomas-Walters et al., 2019). Although factors that drive conservation behaviors *to reduce wildlife crime* have not specifically been studied before, research from natural resource management and human dimensions of conservation suggests that willingness to donate or pay for conservation may be influenced by factors such as values, subjective norms, attitudes, environmental worldviews, and personal norms (Ateş, 2020; Cárdenas & Lew, 2016; López-Mosquera et al., 2014; López-Mosquera & Sánchez, 2012; Martín-López et al., 2007b; Sánchez-García et al., 2021; Wakita et al., 2019). These are some of the main constructs within two social-psychological theories that have successfully been used to explain environmental behaviors consistently: the theory of planned behavior (TPB) (Ajzen, 1991) and the value-belief-norm theory (VBN) (Dietz et al., 2005; Stern et al., 1999).

In this dissertation, I contend that donating money to conservation organizations to help reduce wildlife crime represents the kind of environmental behavior that may be explained by the intention-based premise of the theory of planned behavior (TPB) (Ajzen, 1985, 1991), or by the pro-social motive premise of the value-belief-norm theory (VBN) (Dietz et al., 2005; Stern et al., 1999). In comparing and contrasting the explanatory power of the theory of planned behavior (TPB) with the value-belief-norm theory (VBN), and by using structural equation modeling to evaluate how the main constructs in both these models operate together, I demonstrate whether and to what extent the planned behavior and value-belief-norm models can be applied to studying conservation behaviors for reducing wildlife crime – a novel context and application for both these theories.

In addition to testing the full TPB and VBN models, I will examine the relationship between wildlife value orientations and wildlife crime-related environmental behaviors as evidence from research on human dimensions of wildlife suggests that wildlife value orientations (WVOs) can predict wildlife-related attitudes and behaviors (Manfredo, Teel, Carlos, et al., 2020; Teel et al., 2007b; Teel & Manfredo, 2010). I will also examine whether WVOs may be a stronger, more accurate measure of ecological worldviews in this wildlife crime-related context, compared to the New Ecological Paradigm (Dunlap, 2008) largely used to assess ecological worldviews in the VBN model.

As most environmental social science research has tended to focus on Western and developed countries, it has left many countries in which issues like wildlife crime are widespread under-represented in scholarship. By testing the two theories in a cross-national survey in India and the U.S.A., I will provide new empirical evidence of how well the theory of planned behavior (TPB) and the value-belief-norm theory (VBN) can explain donation behaviors among Indian and U.S. respondents, specifically, as they relate to reducing wildlife crime. The cross-national nature of this dissertation and the application of a communication-based approach to the study of wildlife crime-reduction help to advance and expand the purview of environmental communication scholarship from a more diverse and comparative perspective (Cordano et al., 2011; Thaker, 2021). This dissertation will also add to the small but growing body of work in conservation social science, particularly as it relates to communication and wildlife crime (Bennett et al., 2017; Giannetta, 2017; Megias et al., 2017; Militz & Foale, 2017; Nijman & Nekaris, 2017).

Objectives and Intellectual Merit

The knowledge gaps that this dissertation addresses are: 1) The lack of communication-based research on wildlife crime prevention; 2) The lack of representation of non-Western audiences in interdisciplinary social scientific research on wildlife crime; 3) The identification of salient social-psychological factors that may drive wildlife crime-reducing conservation behaviors and may influence the success of conservation communication campaigns aimed at combatting wildlife crime.

The broad objectives of this dissertation are to: 1) Determine the theoretical structure of behaviors linked to reducing wildlife crime, such as donating money to conservation organizations ; and 2) Explore how findings differ in an international sample of respondents from India and the U.S.A.

The key contributions of this dissertation are that – 1) The survey provides new empirical evidence of the salient beliefs, values, attitudes, norms, and intentions related to wildlife crime prevention which will help determine the theoretical structure of conservation behaviors to reduce wildlife crime; 2) A cross-national comparison adds new knowledge by examining a non-Western perspective on an issue largely under-studied by communication scholars globally (Takahashi, Duan, et al., 2021); 3) The theoretical comparison demonstrates how well two widely-applied theories of environmental behavior – the TPB and VBN – explain donation intentions in the novel context of wildlife crime reduction; and how each theory performs in a cross-national sample; and 4) Whether wildlife value orientations (WVOs) can replace the New Ecological Paradigm scale (NEP) as a measure of ecological worldviews, specifically in the context of wildlife-related behaviors as predicted or explained by the value-belief-norm (VBN) model (Manfredo, Teel, Don Carlos, et al., 2020).

Dissertation Outline

This dissertation consists of five chapters including this introduction chapter. Chapter two provides an in-depth review of interdisciplinary literature relevant to the primary questions posed in this dissertation. Chapter three presents the methods, measures, and analytical approaches along with expected outcomes. Chapter four presents the results of the statistical analyses, and the last chapter discusses the implications of these findings for theory, practice, and future research. Supplemental materials are included in appendices that follow the discussion, while a list of references cited is provided at the end.

CHAPTER TWO: LITERATURE REVIEW

In this chapter, I synthesize research from mass communication, natural resource management, criminology, conservation biology, environmental psychology and social psychology that helps set the stage for understanding the scientific foundations of a behavior such as donating money to conservation organizations for reducing wildlife crime. First, I review the limited research there currently is on conservation communication to identify the gaps that this dissertation helps fill. Next, I discuss the two main theoretical frameworks applied and tested in this dissertation: the theory of planned behavior, and the value-belief-norm theory. In comparing the two theories, I identify the variables of interest and provide conceptual definitions for key constructs. I then provide an overview of the state of wildlife crime as a global issue but more specifically, its prevalence in the two countries studied in this dissertation: India and the United States. I demonstrate why it is necessary to study conservation behaviors associated with reducing wildlife crime. Finally, I describe wildlife value orientations and situate them within the broader goal of this dissertation while outlining how this construct can potentially enhance the predictive and explanatory power of the value-belief-norm theory – thereby testing a potential modification of the theory in a cross-national survey.

Conservation Messaging and Intentions to Donate to Wildlife Crime Reduction

In a meta-analysis on conservation messaging literature, Kidd et al. (2019) found that one of the primary outcome variables in journal articles on conservation messaging was raising funds, and another was encouraging behavior change. Additionally, they found that most experimental studies only measured intentions to donate despite how much conservation organizations rely on actual donation behavior or actions from their stakeholders (Thomas-Walters et al., 2020). This dissertation while also identifying factors that may play a significant role in explaining monetary donation intentions – does so specifically in the context of reducing wildlife crime, so that future research can build on the findings in this dissertation to measure actual monetary donation behavior as an outcome variable and determine which factors drive that behavior in diverse regions and how.

In one of the few studies on this topic, Giannetta (2017) used a relatively small convenience sample to administer surveys in the United States to examine whether communicating the complex nature of wicked problems such as wildlife crime can increase the perceived importance of such an issue. The surveys tested messages that included contextual information about how the poaching of African elephants for their ivory has been associated with social conflict, terrorism, violence, and human rights issues etc., and simple messages including a one-line statement on how the poaching of African elephants for their ivory was pushing them towards extinction. While a larger number of respondents ranked the contextual message as being very and highly important, there was no statistical difference between the messages. However, it is worth noting here that this was not an experimental study, and potential confounds were not addressed or accounted for. For instance, U.S. survey respondents could be subject to the effects of psychological distance when considering messages about African elephants and orangutans in Southeast Asia; there could be boomerang or psychological reactance effects or priming effects to the detailed message about converging crimes and threats; and the contextual message on social, political, and economic harms associated with wildlife crime could also have been processed in a way that made respondents feel like there was nothing they could do to help address the issue. While these findings are not generalizable, I contend that Giannetta's study is a step in the right direction because not only does it acknowledge that communication about issues such as wildlife crime will likely need to acknowledge and address the wicked nature of this issue by making the non-environmental aspects (e.g., economy, health, conflict, justice, politics, etc.) salient to audiences, but it also provides important empirical insight into how respondents – even a small sample of them – are likely to perceive the importance of an issue such as poaching/wildlife crime when communicators make decisions to include or exclude specific information. Giannetta (2017) therefore, provides a helpful block on which future cross-national and experimental research examining the role of communication in influencing the adoption of conservation behaviors linked to reducing wildlife crime can be built, thereby facilitating a greater understanding of the social-psychological factors that may drive or dampen individuals' intentions to donate money to conservation organizations for reducing wildlife crime in response to conservation messaging.

As communication-based research on wildlife crime-reducing conservation behaviors is only beginning to scratch the surface of this area of scholarship, to begin explaining donation intentions to reduce wildlife crime, I turned to research from natural resource management, conservation social science, and human dimensions of wildlife that has examined a 'close cousin' pair of constructs – willingness to pay and willingness to donate to wildlife conservation. In doing so, I found that factors from two widely applied social psychological theories of environmental behavior – the theory of planned behavior (TPB) (Ajzen, 1991), and the value-belief-norm theory (VBN) (Stern et al., 1999) – have consistently been associated with these conservation donation intentions.

For instance, studies on psychometric predictors of willingness to pay suggest that altruistic and biospheric values, and subjective norms positively influence willingness to pay for the environment (Wakita et al., 2019). Attitudes have also been identified as a significant driver of willingness to donate to conservation (Martín-López et al., 2007a). Environmental worldviews, such as those represented by the New Ecological Paradigm, as well as beliefs about ascribed responsibility have been associated with willingness to pay for conservation (Cárdenas & Lew, 2016). Primary constructs from both the planned behavior and the value-belief-norm models – such as attitudes, perceived behavioral control, subjective norms, value orientations, beliefs, and personal norms – have all been significantly associated with willingness to pay in an environmental context (Ateş, 2021; López-Mosquera, 2016; López-Mosquera et al., 2014; López-Mosquera & Sánchez, 2012; Sánchez-García et al., 2021).

Thus, a logical starting point for explaining intentions to donate money to conservation organizations for reducing wildlife crime is to apply these two validated behavioral theories to this novel context of wildlife crime reduction, and assess the explanatory power of each theory, eventually identifying the potential for developing an integrated model that may offer a more enhanced predictive potential (Klöckner, 2013).

Comparing Two Theories of Environmental Behavior

Environmental behaviors can be planned or unplanned. Primarily, existing explanations of environmental or pro-environmental behaviors have been offered through either the planned behavior (TPB) lens which suggests that intentions are the closest predictors of behaviors (Ajzen, 1991), or the value-belief-norm (VBN) lens which suggests the pro-social motives or norms are the closest determinants of environmental behaviors

(Dietz et al., 2005; Stern et al., 1999). Over the years, research has also suggested that environmental behaviors might be a composite of both rational-thinking (intentions) and pro-social motives (Bamberg & Möser, 2007; Klöckner, 2013; Steg et al., 2014; Steg & Nordlund, 2018).

Given the lack of prior research in this area, however, we do not currently know which of these factors can explain or predict conservation behaviors to reduce wildlife crime, such as donating money to conservation organizations. Therefore, to build new knowledge on factors explaining such behaviors, I begin by comparing the theory of planned behavior (Ajzen, 1991) and the value-belief-norm theory (Dietz et al., 2005; Stern et al., 1999) to understand how well these two theories explain donation intentions to help reduce wildlife crime in a cross-national sample of participants.

In the following section, I present a review of the two theories, their key constructs, the conceptual definitions, and a critical analysis of how these theories relate to and complement one another.

Theory of Planned Behavior

The theory of planned behavior (TPB) (Ajzen, 1991) suggests that factors related to self-interest, such as positive attitudes toward a behavior, favorable social normative perceptions about a behavior, and greater perceived behavioral control increase an individual's intentions to perform a behavior (Ajzen, 1991; Kaiser et al., 2005). Figure 1 shows the primary constructs in the TPB and the relationships between these constructs and behavior.

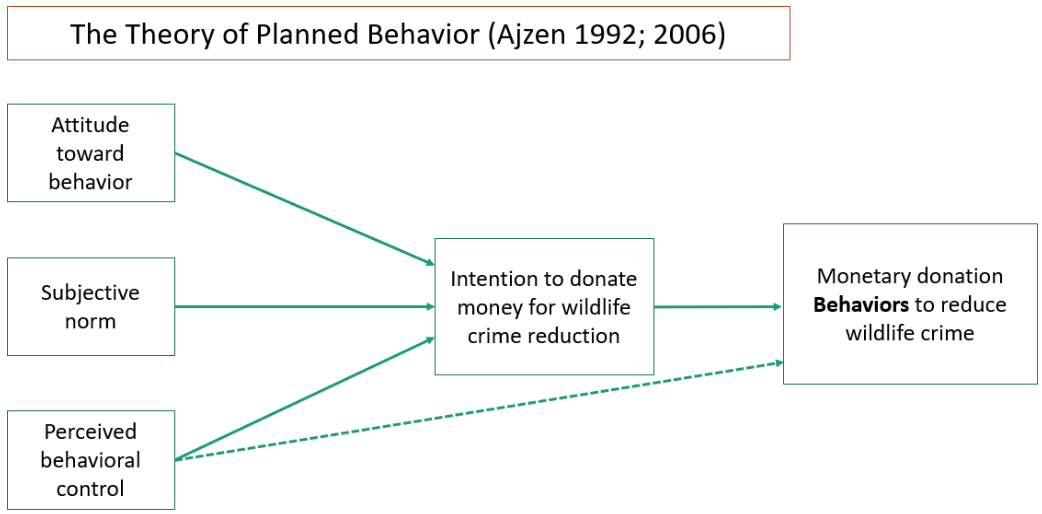

Figure 1 - Conceptual model of the theory of planned behavior

Behavioral beliefs are defined as “beliefs about the likely consequences of the behavior” (Ajzen, 2006, p.1), and outcome evaluation beliefs are defined as the extent to which the behavioral outcome is evaluated as good or bad (Ajzen, 2006). Together, behavioral and outcome evaluation beliefs influence attitudes. Attitudes towards the behavior are defined as “the degree to which a person has a favorable or unfavorable evaluation or appraisal of the behavior in question,” (Ajzen, 1991, p.188); they reflect the positive or negative evaluations of the target behavior and its outcomes (Ajzen, 2006; Kaiser et al., 2005; López-Mosquera & Sánchez, 2012).

Normative beliefs are defined as beliefs about the normative expectations of others (Ajzen, 2006, p.1), and they refer to both injunctive as well as descriptive normative beliefs. The latter describes the extent to which an individual believes that people close to them are performing the behavior in question. If a person believes that those who are important to them would approve of them performing a behavior, they would be more likely to perform it (Kaiser et al., 2005). Motivations to comply are described as the extent to which an individual wants to comply with the injunctive norms of their referent group or the people important to them (Ajzen, 2006; Montaño & Kasprzyk, 2008). Together, normative beliefs and motivations to comply influence subjective norms which can be described as the strength of one's perceptions that those relevant to them expect them to perform the behavior (Ajzen, 2006; López-Mosquera & Sánchez, 2012). Ajzen (1991, p.188) defines subjective norms as "the perceived social pressure to perform or not to perform the behavior."

Control beliefs, or beliefs about the presence or absence of certain factors that may facilitate or impede behavioral performance and the perception that a salient control factor will enable or inhibit a person's ability to perform the behavior together determine perceived behavioral control (Ajzen, 2006; Montaño & Kasprzyk, 2015). Perceived behavioral control is described as "the perceived ease or difficulty of performing the behavior," (Ajzen, 1991, p.188) which is expected to "reflect past experience as well as anticipated impediments and obstacles" to performing the behavior (Ajzen, 1991, p.188; Han, 2015; López-Mosquera & Sánchez, 2012).

Behavioral intention, the closest predictor of behavior as per the TPB, is described as the willingness to perform the target behavior (Ajzen, 1991; Kaiser et al., 2005). In this dissertation, behavioral intention is conceptually defined as "an indication of how hard people are willing to try, of how much of an effort they are willing to exert, in order to perform the behavior," (Ajzen, 1991, p.181; Han, 2015).

While this model of intentional behavior has received consistent and strong empirical support, it has been criticized for undervaluing the role of morality or personal norms in predicting environmental behavior (Klöckner, 2013).

While this model of intentional behavior has received consistent and strong empirical support, it has been criticized for undervaluing the role of morality or personal norms in predicting environmental behavior (Klöckner, 2013).

Value-Belief-Norm Theory

The value-belief-norm theory (VBN), an extension of Schwartz's (1977) work on norm activation suggesting that people behave altruistically when they feel morally obligated to do so, posits that environmental behaviors are a product of pro-social factors such as values, ecological worldviews, outcome expectations, problem awareness, and personal norms (Dietz et al., 2005; Schwartz, 1977; Stern et al., 1999).

Schwartz (1977) suggested that for people to act out of moral obligation, their personal norms have to be activated which requires that four conditions be met – one must be aware of the need for help; one must be aware of the consequences of the behavior in question for those in need; one must accept responsibility to act; and one must believe they are capable of performing the helpful behavior (Klöckner, 2013). Experts have suggested that these relationships explaining altruistic behavior also apply to explaining environmental behaviors because, as Thøgersen argues, environmental behaviors are a kind of moral behavior so they should not be conceptualized as an outcome of simple cost-benefit analyses, but rather, as also being driven by moral beliefs (Thøgersen, 1996).

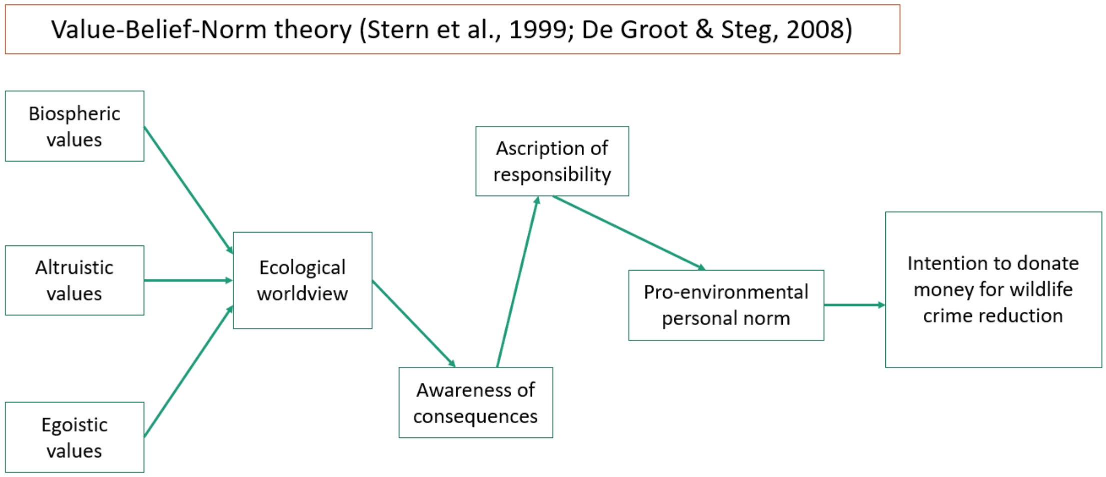

Figure 2 - Conceptual model of the value-belief-norm theory

The VBN, therefore, suggests that environmental behaviors that align with one's normative pressures or expectations are likely to be performed when the person feels morally responsible for the outcomes and is aware of the consequences of action or inaction (van Riper & Kyle, 2014a; Carfora et al., 2021).

Conceptually, values can be defined as beliefs related to a desirable end state or behavior that transcend specific situations, serve as guiding principles when it comes to selecting or assessing behaviors, and vary in their levels of importance (Han, 2015; Schwartz, 1992, p.4). The importance of values to environmental behaviors has been repeatedly established (De Groot & Steg, 2008; Gkargkavouzi et al., 2019; Steg et al., 2005; Stern et al., 1999; van der Werff & Steg, 2016), yet their ability to explain or predict conservation behaviors to reduce wildlife crime remains unknown. According to the VBN, people whose values align with the outcome or behavior, those who believe that valued objects are threatened and that their actions – or lack thereof – can help alleviate those threats, and those who feel morally obligated to take action, are more likely to perform a behavior (Gkargkavouzi et al., 2019; Steg et al., 2005; Stern et al., 1999). The VBN model includes five dimensions of values of which three are tested in this dissertation. These are –

a) *Biospheric values* focus on the benefits of environmental behaviors to non-human species and the biosphere such that individuals with this value orientation believe that protecting nature and environmental conservation are important (De Groot & Steg, 2008; Stern et al., 1999; van Riper & Kyle, 2014a). Dimensions of biospheric values include prevention of pollution, respecting the earth, unity with nature, and protecting nature (De Groot & Steg, 2008);

b) *Altruistic values* focus on other humans and society itself such that individuals with altruistic value orientations value the benefits of environmental behaviors for other people (Stern et al, 1999). The dimensions of altruistic values include equality, world peace, social justice, and social welfare (De Groot & Steg, 2008); and

c) *Egoistic values* are related to self-interest such that individuals with this value orientation value environmental behavior for benefit to oneself, one's personal well-being, or one's family and friends. Individuals with egoistic values are likely to act pro-environmentally when the benefits of an environmental behavior outweigh the perceived costs (Jansson et al., 2010; Stern et al., 1999; van Riper & Kyle, 2014a). Dimensions of egoistic values include social power, wealth, authority, and influence (De Groot & Steg, 2008).

The VBN theory suggests that biospheric and altruistic values are positively related to ecological worldviews, while egoistic values are negatively related to ecological worldviews (Gkargkavouzi et al., 2019). Ecological worldviews are described as overarching beliefs about the relationship between humans and the natural environment (Steg et al., 2005; Stern et al., 1999) which are positively associated with an individual's predisposition to act pro-environmentally (Han, 2015). Most prior research has operationalized ecological worldviews by determining the extent to which an individual subscribes to the New Ecological Paradigm (NEP), thereby measuring this concept with the widely used NEP scale (Dunlap et al., 2000; van Riper & Kyle, 2014a). In the VBN model, ecological worldviews are conceptualized as being positively associated with awareness of consequences – a concept I explicate next.

Within VBN-related literature, the concept of awareness of consequences has been defined inconsistently. While some researchers have described it as one's awareness of the adverse consequences of events for valued objects (Kaiser et al., 2005; Stern et al, 1999), the manner in which this conceptualization has been characterized operationally and measured has been very similar to how the concept of attitudes within TPB has been defined, operationalized, and measured at times. Addressing these inconsistencies, Klöckner (2013) says that, "Empirically speaking, awareness of need and awareness of consequences often blend together, which has led to several researchers either using awareness of need or awareness of consequences in their studies," (pp.10). Since this dissertation is a comparison of the TPB and the VBN, establishing discriminant validity is especially crucial. Therefore, awareness of consequences – in this dissertation – is conceptualized in line with Han's (2015) definition – as one's awareness of adverse consequences *to* valued objects – which has sometimes been labelled, and indeed, operationalized as awareness of problems or problem awareness (Bamberg & Möser, 2007;

Han, 2015; Steg & Nordlund, 2018; Ünal et al., 2019; van der Werff & Steg, 2016; van Riper & Kyle, 2014a).

In VBN's sequential chain of factors predicting environmental behaviors, awareness of consequences is positively associated with ascription of responsibility – which refers to one's belief that they are responsible for negative consequences that may result from not acting pro-environmentally (Gkargkavouzi et al., 2019; Han, 2015). Others have described ascription of responsibility as the belief of the denial that one's actions have either caused or helped alleviate negative consequences to valued objects or others (Stern et al., 1999). Van Riper & Kyle (2014) suggest that whether a person believes they can make a difference and/or whether they believe that other people are not doing the needful also describes ascription of responsibility. Still others have conceptualized it as 'felt responsibility,' described as beliefs about the extent to which a person feels compelled to take action to obtain a desired result (Kaiser et al., 2005; Munson et al., 2021).

Finally, VBN suggests that ascription of responsibility is positively associated with personal norms – often interchangeably referred to in the literature as 'moral obligations.' In the context of environmental behaviors, personal norms are conceptually defined as a sense of moral obligation to act pro-environmentally (Han, 2015). Influenced by an individual's value orientations and belief structures, personal norms determine whether or not an individual feels they ought to or are obligated to engage in an environmental behavior (Gkargkavouzi et al., 2019; van Riper & Kyle, 2014a). Unlike subjective norms in TPB which refer to what an individual thinks other people would expect them to do, personal norms within VBN reflect self-expectations (Kaiser et al., 2005; Schwartz, 1977; Stern et al., 1999).

Like the TPB model, the VBN has also received substantial empirical support for its ability to explain environmental behaviors. However, with its emphasis on personal norms, values and beliefs, the VBN leaves out crucial other determinants of environmental behaviors such as perceived behavioral control, social norms, and attitudes (Klöckner, 2013).

Relationships Between TPB and VBN Constructs

In addition to comparing the planned behavior (TPB) and value-belief-norm (VBN) models in their ability to explain intentions to donate money to reduce wildlife crime, this dissertation also considers the relationships between constructs of the two theories that prior research has found to determine the scope for proposing a more comprehensive, if integrated, approach to explaining conservation behaviors aimed at reducing wildlife crime.

Previous research has found that TPB's key constructs – attitudes, subjective norms, and perceived behavioral control – are strongly related to VBN's constructs – awareness of consequences and personal norms (Han, 2015). It has also been suggested that individuals who are aware of the consequences or seriousness of environmental problems may be more likely to have positive environmental attitudes; awareness of consequences may also have a direct positive impact on subjective norms and perceived behavioral control; and subjective norms may be positively associated with inducing personal norms (Han, 2015).

However, research comparing the theories has shown mixed results. While several studies have found that TPB more strongly predicted environmental behaviors (López-Mosquera & Sánchez, 2012), others have underscored the importance of the values and personal norms-based VBN model as well (Kaiser et al., 2005). Even in the context of conservation behaviors specifically, scholars have highlighted the role of values, beliefs, ecological worldviews, and personal norms in predicting environmental behaviors (Jansson et al., 2010).

Both the TPB and VBN models are largely missing from the communications-based scholarship on conservation behaviors to reduce wildlife crime. This dissertation is, therefore, grounded in the literature reviewed above, presenting and discussing findings from a survey questionnaires designed based on the constructs in both the planned behavior (Ajzen, 1991) and value-belief-norm models (Stern et al., 1999). In addition to providing new empirical evidence of salient social-psychological factors likely to explain intentions to donate to conservation organizations for reducing wildlife crime, the findings from this dissertation will aid in the future development of an integrated model that can be tested in subsequent experimental research.

Cross-national Wildlife Crime

As mentioned in the previous chapter, wildlife crime is a kind of wicked problem whose far-reaching effects go beyond just environmental impacts and influence various aspects of our lives such as public health, economic and political stability, governance, development, and peacekeeping efforts (Giannetta, 2017; Kurland et al., 2017; McNamara et al., 2016; Veríssimo & Wan, 2019).

Geopolitically, both India and the United States are significant players in the fight against wildlife crime. For instance, the U.S. is a major consumer market for illegal wildlife, parts, and products, including those such as tiger skins, tiger bones etc. that may originate in India when tigers are poached (illegally hunted) in their native wild habitats. India, therefore, is a major source country where wildlife is not only poached and smuggled, but where multiple species including tortoises, marine animals, pangolins, leopards, rhinos, etc. are vulnerable to the illegal wildlife trade, often being trafficked across borders to destination countries (Khanwilkar et al., 2022).

In India and the United States, multiple agencies such as the Wildlife Crime Control Bureau and the US Fish and Wildlife Service, respectively, are involved in multiple national and international operations to gather intel, enforce laws, and collaborate globally on efforts to combat illegal wildlife trade and mitigate its effects (UNODC, 2020). Given the presence and the importance of the issue in both these countries, multiple conservation organizations operating within India and the U.S. also run conservation campaigns to educate the public about the issue of wildlife crime and to persuade audiences to engage in the conservation behaviors called for in these campaigns or in other communication.

Therefore, I contend that it is crucial to examine how people from both these countries think and feel about the issue of wildlife crime and behaviors linked to reducing it. Given the lack of previous research examining social-psychological factors linked to wildlife crime prevention, this dissertation makes no assumptions about levels of awareness among U.S. and Indian participants regarding wildlife crime itself, nor regarding participants' prior knowledge of contemporary conservation issues, endangered species, etc. when assessing their responses to the survey.

Both theoretically, as it relates to understanding the structure of conservation behaviors that reduce wildlife crime, and empirically, as it relates to discovering drivers of donation intentions to reduce wildlife crime, the cross-national comparison of both empirical data and theoretical models in this dissertation make valuable contributions towards advancing international environmental communication scholarship (Takahashi, Metag, et al., 2021).

As some scholars have found, country-level differences such as affluence, income inequality, education levels, and cultural values can influence environmental behaviors either directly, or through other social-psychological drivers such as a perceived behavioral control (Aral & López-Sintas, 2021). Others suggest that cross-national differences in family values, social structure and social norms can influence the extent to which people feel connected to nature – which itself, has been associated with ecological worldviews, environmental concern, and environmental attitudes (Clayton et al., 2021; Oh et al., 2021).

In their cross-cultural analysis of the links between modernization (wealth, education, and urbanization), anthropomorphism, and attitudes towards wildlife, Gómez-Melara et al. (2021) found that the association between anthropomorphism, positive attitudes and intentions towards wildlife was universal across the five countries in which they surveyed participants – Brazil, Indonesia, Malaysia, Mexico, and Spain – but there were culturally mediated relationships that contribute to them echoing the underlying argument I make in this dissertation – that generalizing research findings from Western industrialized countries to inform conservation communication, campaigns or policies globally can misfire and should be done with extreme caution.

Gómez-Melara et al. (2021) based their work on pioneering previous research establishing the relevance of studying wildlife value orientations – which are associated with conservation attitudes and behaviors – and are reviewed next.

Wildlife Value Orientations

Teel et al. (2007) define wildlife value orientations as "basic beliefs that give personal meaning of right and wrong and an ideal life to one's more basic values in relation to wildlife," (p.300). Broadly, this construct is described as "enduring beliefs regarding wildlife", (*What Are Wildlife Value Orientations?*, n.d.).

Theoretically, wildlife value orientations are grounded in the value-attitude-behavior or cognitive hierarchy model, and as such, the construct of wildlife value orientations suggests that "individual behavior toward wildlife is driven by specific attitudes, and these attitudes are directed by wildlife value orientations," (Teel et al., 2007, p.300). It is important to point out here that the characterization of wildlife value orientations as influencing 'specific attitudes' which are then responsible for influencing wildlife-related behaviors, aligns with how the theory of planned behavior framework (Gkargkavouzi et al., 2019; Kaiser et al., 2005; López-Mosquera et al., 2014) conceptualizes the relationship between attitudes and behavior – that attitudes must be as specific as possible and must correspond as closely as possible to the behavior being assessed for them to be an effective and reliable predictor of that behavior. Given that one of the objectives of this dissertation are to identify salient social-psychological drivers of wildlife-related behaviors – like donating money to reduce wildlife crime – I contend that wildlife value orientations are likely to play a significant role as drivers of attitudes towards wildlife crime-reducing behaviors, and as a more accurate assessment of how participants from India and the U.S. see their relationship with wildlife compared to the general nature of beliefs captured by the New Ecological Paradigm scale.

Broadly, there are two dimensions of wildlife value orientations – a domination value orientation, and a mutualism value orientation – each of which have two facets within them that reflect these constructs theoretically. Domination value orientations emphasize a hierarchical division between humans and non-humans and are suggested to lead to a utilitarian or anthropocentric attitude to wildlife which prioritizes human welfare. Mutualism orientations emphasize that humans and non-human animals are part of the same group, that wildlife deserves rights, and that humans and wildlife should co-exist in harmony. Mutualistic beliefs generally lead to more positive attitudes that prioritize co-existing with wildlife (Gómez-Melara et al., 2021; Teel et al., 2007b). Research has shown that males and older people are more likely to have domination value orientations whereas females and urban residents are more likely to have mutualistic value orientations than rural dwellers and males (Gómez-Melara et al., 2021).

In their cross-cultural assessment of wildlife value orientations, Teel et al. (2007) found that mutualism value orientations were more frequently expressed in the Netherlands, Thailand, and Estonia than domination orientations; a mixture of mutualism and domination was found in Mongolia; whereas domination value orientations were most common in China. Prior work suggests that, as part of a larger shift in values, wildlife value orientations in the United States have shifted from a domination-oriented focus to a being more mutualistic and rooted in various cultural influences which, in turn, influences attitudes towards wildlife (Jacobs et al., 2018a; Manfredo et al., 2016; Teel et al., 2007b).

Research also indicates that wildlife value orientations may mediate the relationship between general values and wildlife-related attitudes and norms (Jacobs et al., 2018a; Manfredo, Teel, Don Carlos, et al., 2020; Manfredo, Urquiza-Haas, Don Carlos, et al., 2020).

However, as Teel et al. (2007) point out, there is very little scholarship on a global, cross-national level on the cognitive determinants of human-wildlife relationships. Moreover, although research on cross-national wildlife value orientations is limited, it has not yet looked at how these value orientations manifest in India – a country in which wildlife-related conservation programs, issues, policies, crimes, and enforcement are by no means trivial in severity and scale, and one in which theories of environmental communication and environmental psychology are not commonly applied or tested in.

Manfredo et al. (2009) underscore the importance of understanding global wildlife value orientations and their relationship with culture:

> *"Every culture's relationship with wildlife is a response to universal human needs (e.g. food, protection, reproduction), and across cultures, both differences and similarities exist in how these needs have been met. Cross-cultural study of human-wildlife relationships reveals these differences and similarities, providing important information for wildlife managers who increasingly operate in a global context," (p. 31).*

In this dissertation, I therefore contend that assessing wildlife value orientations is important because without understanding the social context in which conservation programs and communication or campaigns to combat wildlife crime are run, it would be difficult to accurately evaluate the success and impacts of those campaign communications (Teel et al., 2007b).

Wildlife Value Orientations as a Measure of Ecological Worldviews

Due to the close correspondence between wildlife value orientations and wildlife-related attitudes and behaviors, and given how they are conceptualized and measured, I argue that wildlife value orientations may be a more accurate construct for measuring ecological worldviews and, thereby, may perform better than the New Ecological Paradigm scale (Dunlap et al., 2000) at explaining or predicting those environmental behaviors that are related to wildlife and its conservation.

Within the value-belief-norm framework (Stern et al., 1999; Stern & Dietz, 1994), ecological worldviews are conceptualized as general beliefs that people have about their relationships with the environment (van Riper & Kyle, 2014a), or in other words, as our beliefs about human-nature interactions (Gkargkavouzi et al., 2019).

As van Riper & Kyle (2014) point out, the New Ecological Paradigm scale (NEP) that is frequently used to measure ecological worldviews within the VBN model, is "theoretically related to principles about living in harmony with or having mastery over natural and social worlds," (p.289). The worldviews represented by the NEP scale are also described as being "situated along a continuum anchored by biocentric beliefs oriented toward environmental protection and anthropocentric beliefs geared toward people taking precedent over nature," (van Riper & Kyle, 2014, p.289).

The operationalization of the New Ecological Paradigm – a 15-item scale – has been demonstrated to tap into five underlying latent dimensions – balance of nature; limits to growth; anti-exemptionalism; eco-crisis; and human domination – each of which is measured using three items (Amburgey & Thoman, 2012). While a shorter 6-item version of the scale has been used in prior research which taps into three of those five underlying dimensions of ecological worldviews (van Riper & Kyle, 2014a), the key takeaway here is that the New Ecological Paradigm scale does not measure a unidimensional construct although a substantial number of studies have applied it as one. When a confirmatory factor analysis was used to assess the theoretical structure of the NEP scale, not only did the five distinct dimensions mentioned above emerge, but researchers found that the NEP was best represented as a second-order factor structure construct in which the five underlying latent dimensions are correlated scales measured by three indicators each (Amburgey & Thoman, 2012).

Wildlife value orientations also have two underlying dimensions – domination and mutualism – that are conceptually and operationally similar to the way in which the NEP scale is organized (Vaske et al., 2011). Respondents scoring higher on the eco-centric belief items on the NEP scale will be identified as having stronger ecological worldviews – which is similar to the mutualism wildlife value orientations, and those with lower NEP scores will be identified as having utilitarian or human-centered beliefs – which is similar to having domination wildlife value orientations (Amburgey & Thoman, 2012; Dayer et al., 2007; Dunlap, 2008; Dunlap et al., 2000; Fulton et al., 1996; Gómez-Melara et al., 2021; Liordos et al., 2021; Ntanos et al., 2019).

Essentially, I argue, both wildlife value orientations and the NEP scale represent a general set of beliefs – one about how people perceive their relationship with wildlife (Teel et al., 2007b), and the other about how people perceive their relationship with the environment more broadly (van Riper & Kyle, 2014a). Further, as Vaske et al. (2011) point out, wildlife value orientations that stem from the cognitive hierarchy framework, reflect ideologies, and therefore, I contend, that they are conceptually and theoretically an adequate and appropriate replacement of the NEP scale – itself a set of ecological ideologies or beliefs.

Finally, I posit in this dissertation that as wildlife value orientations assess beliefs about wildlife specifically, they will be more closely related to and a better measure of wildlife-related behaviors, and may enhance the explanatory power of the value-belief-norm model (VBN) as a replacement of the NEP's general environmental beliefs (X. Liu et al., 2018; Stern et al., 1999; Stern & Dietz, 1994). This dissertation examines the scope for wildlife value orientations to explain wildlife crime-reducing conservation behaviors as part of the VBN framework, and further adds new knowledge by providing empirical data on wildlife value orientations cross-culturally which itself is a crucial merit of this dissertation because no information currently exists about wildlife value orientations in India whereas there have been several studies assessing these beliefs in the United States.

Research Questions

Aligned with the broad objectives outlined in Chapter One, and guided by the relevant literature reviewed in this chapter and by preliminary work, this dissertation seeks to answer the following research questions:

- ***RQ 1:*** Which social-psychological factors best explain donation intentions to help reduce wildlife crime?
- ***RQ 2:*** How do the responses of participants from India compare to those of participants from the U.S.A.?

CHAPTER THREE: METHOD, MEASURES, AND ANALYSIS

Survey Design, Sampling, and Procedure

To answer the two research questions aimed at understanding existing values, attitudes, beliefs, and norms related to conservation behaviors for wildlife crime reduction, I conducted an online survey hosted on Qualtrics, recruiting a total of 2,000 participants of which 1,000 participants were recruited from India and 1,000 from the United States. The samples were recruited such that they were representative of latest available census data from both countries; the criteria for quota-matching were age, gender, and income. This dissertation research has been approved by the IRB at Michigan State University.

The survey included questions based on both, the theory of planned behavior (Ajzen, 1991), and the value-belief-norm model (Stern et al., 1999; Stern & Dietz, 1994). Specific survey items are discussed in the following section. Participants were first asked to indicate whether they were above the age of 18. Participants were then introduced to the study and its objectives, as well as informed of their data remaining anonymous and their right to withdraw from participating without penalty at any time. Participants continued with the survey only if they granted informed consent. Three other enforced checks were used throughout the survey to ensure data quality – two attention checks and one speeding check. Participants who failed either one of the attention checks and those who completed the survey in under 10 minutes were removed from the final sample retained for analysis. For the U.S. survey, N = 900 participants were retained in the final sample after 615 participants failed the first attention check, 287 failed the second attention check, 583 were removed for speeding, 286 were underage, and 134 did not grant informed consent. For the India survey, N = 920 participants were retained for the final analysis after 770 failed the first attention check, 330 failed the second attention check, 504 were removed for speeding, 156 were underage, and 147 did not consent to participate.

For both the India and U.S. surveys, 10% of the study sample was designated for the pilot test. Therefore, of the total *N* = 1,000 participants recruited from each country by Qualtrics, *N* = 900 were part of the final study and *n* = 100 were part of the pilot study for the U.S. survey, whereas *N* = 920 were part of the final study and *n* = 98 were part of the pilot study for the India survey.

Given that both the theory of planned behavior and value-belief-norm theory have not previously been applied to a study of conservation behaviors specific to reducing wildlife crime, there are no standardized scales, validated measures, or adaptable surveys that could have been used in this dissertation. This necessitated both a pre-test in which the survey instrument was tested among a group of peers, colleagues, and social scientists, and some follow-up interviews with them to gain a deeper understanding of respondents' perceptions of the survey questions, their ability to understand them in the same way, and to identify potential sources of response error or confusion among participants (Collins, 2003). I began by conducting interviews with peers to pre-test the questionnaire and identify potential issues with order effects, understandability, etc. (Collins, 2003; Haeger et al., 2012). Using feedback from these interviews, I made requisite changes to question and response option wording and phrasing before conducting the pilot test, which I elaborate on later in this chapter.

Sample

Overall, for the final surveys, the sample consisted of *N* = 1,820 respondents, all of whom were above the age of 18 and were residents of either India or the United States. An *a priori* power analysis showed that I would need at least 450 participants from each country. However, this study was conducted using a larger sample of respondents given an existing contract with Qualtrics. Table 1 shows the age and gender distributions of participants from both countries.

Table 1 - Age and gender frequency distributions of respondents from India and USA

Age	India		United States of America		Total
	Female	Male	Female	Male	
18 – 24	291	136	103	17	547
25 – 34	92	180	106	50	428
35 – 44	26	80	70	68	244
45 – 54	31	27	116	39	213
55 – 64	22	15	75	81	193
More than 65	12	4	8	167	191
Total	474	442	478	422	1,816

Most participants across both countries were between 18 and 24 years old. Cross-nationally, there were slightly more female respondents than male respondents. Most (76%) of the respondents from India – 80.80% of female participants, and 71.49% of male participants were under the age of 35, whereas 43.72% of female respondents in the USA and 15.87% of men were under the age of 35. Among all the cross-national respondents over the age of 65 (n = 191), 87.43% were males from the USA (n = 167). Two respondents from India identified as non-binary whereas two others preferred not to indicate their gender identification. Tables 2 and 3 indicate the income distributions of participants from both India and the United States.

Table 2 - Income distribution of Indian participants

Income (INR)	India		Total
	Female	Male	
Less than ₹2,50,000	36	92	128
₹2,50,001 to ₹5,00,000	317	124	441
₹5,00,001 to ₹7,50,000	102	81	183
₹7,50,001 to ₹10,00,000	8	50	58
₹10,00,001 to ₹12,50,000	7	47	54
₹12,50,001 or more	4	48	52
Total	473	442	916

Income categories for India reflect that country's national tax bracket categories. Each of the two Indian respondents who identified as non-binary and each of two respondents who did not identify their gender earned less than INR 2,50,000, and between INR 2,50,001 and 5,00,000, respectively. Most Indian women earned less than INR 7,50,000 per year, whereas men had higher incomes and predominantly among those who earned more than INR 7,50,000 per year. For context, based on the exchange rate in mid-August 2022, one U.S. dollar is worth 79.75 Indian National Rupees (INR). Contextualized in terms of U.S. Dollars, most Indian female respondents earned less than $9,500 per year.

Table 3 - Income distributions of US participants

Income (USD)	USA		Total
	Female	Male	
Less than $20,000	253	52	305
$20,001 to $40,000	125	114	239
$40,001 to $60,000	60	85	145
$60,001 to $80,000	30	53	83
$80,001 to $100,000	2	39	41
$100,001 or more	8	79	87
Total	478	422	900

Similar to the gender and income breakdown of the sample of Indian respondents, most U.S. participants who earned less than $40,000 per year were women, and most of those who earned higher incomes were men. Most U.S. participants (76.55%) earned up to $60,000 per year.

Other demographic characteristics that reflect cross-national differences in the study sample include education, employment, and political ideology. Table 4 shows the highest level of education that participants from both countries had completed.

Table 4 - Education levels of participants from India and USA

Education Level	India	USA	Total
No formal education	1	2	3
Primary education (US) SSC/ICSE/CBSE/Grade 10 (IND)	5	22	27
High school diploma (US) Junior college/HSC/Grade 12 (IND)	117	231	348
Vocational, technical, trade school (US) Professional diploma (IND)	37	100	137
Bachelor's degree	439	71	510
Master's degree	292	15	307
Ph.D. or higher	18	3	21
Other	7	27	34
Prefer not to say	4	6	10

Most respondents from India (*n* = 567) and the United States (*n* = 273) were employed either full-time or were self-employed. Table 5 shows the distribution of participants' employment status.

Table 5 - Employment distributions of Indian and U.S. participants

Employment Status	USA	India	Total
Employed full-time/Self-employed	273	567	840
Employed part-time	101	119	220
Intern	2	46	48
Unemployed – looking for work	112	68	180
Unemployed – not looking for work	108	30	138
Retired	210	17	227
Other	86	61	147
Prefer not to say	8	11	19

Most respondents in both India (*n* = 352) and the United States (*n* = 359) identified their political ideologies as neither conservative nor liberal. Among those who identified as very conservative, *n* = 156 were from the United States whereas *n* = 96 were from India. *n* = 173 participants from the U.S. and *n* = 144 participants from India identified as slightly conservative. Among those who identified as slightly liberal, on the other hand, *n* = 193 were from India and *n* = 125 were from the U.S. Finally, *n* = 135 participants from India and *n* = 87 participants from the U.S. identified as very liberal.

Measures

In this section, I outline each item used to measure the theory of planned behavior and value-belief-norm theory constructs, respectively. However, it is worth noting here that no prior validated scales and measures of these constructs exist specifically in the context of wildlife crime reduction. Therefore, I rely on previous research in environmental behavior – even if outside the context of wildlife crime-reducing conservation behaviors – to operationalize the constructs in both theoretical models. Further, given this lack of existing previously validated scales to measure wildlife crime-reducing behaviors, I expect that this dissertation will aid in the development and validation of scales that more closely measure attitudes, norms, beliefs, perceived behavioral control, and intentions related to reducing wildlife crime.

Dependent Variable: Behavioral Intention

Items modified from Carfora et al. (2021b) and Han (2015) were used to measure participants' intentions to donate money to conservation organizations to help reduce wildlife crime. These items were: "I am willing to donate money to conservation organizations over the next month to help reduce wildlife crime"; "I plan to donate money to conservation organizations over the next month to help reduce wildlife crime"; and "I will definitely donate money to conservation organizations over the next month to help reduce wildlife crime." Responses to each of these items were assessed on a scale from 1 = *Strongly disagree* to 7 = *Strongly agree* (see Table 6).

Theory of Planned Behavior

While the conceptual definitions of the constructs measured by the items listed below are outlined in Chapter 2, Table 6 presents the operationalizations and scales/items. The table also indicates which previous literature the measures were derived from and how they were modified to apply to this novel context of conservation behaviors aimed at reducing wildlife crime – a category of environmental behaviors that this theory has not previously been used to examine, creating the absence of valid, reliable, and closely corresponding measures.

Table 6 - Measures of theory of planned behavior constructs

Construct	Measures	References
Attitude towards the behavior	"I think the idea of donating money to conservation organizations to help reduce wildlife crime is" --- • Very positive • Very responsible • Very intelligent • Very useful • Very ecologically helpful (1 = *Strongly disagree*, 7 = *Strongly agree*)	Modified to include the outcome behavior of donating money to reduce wildlife crime López-Mosquera et al., 2014
Subjective norms	"Most people who are important to me think that one should donate money to conservation organizations to help reduce wildlife crime." "Most people who are important to me expect that I will donate money to conservation organizations to help reduce wildlife crime." "Those people whose opinions I value would donate money to conservation organizations to help reduce wildlife crime." (1 = *Strongly disagree*, 7 = *Strongly agree*)	Modified to include the outcome behavior of donating money to reduce wildlife crime López-Mosquera et al., 2014, and Han, 2015. Both cited references use these items.

Table 6 (cont'd)

Perceived behavioral control	"I am confident that if I want, I can donate money to conservation organizations to help reduce wildlife crime." (Han, 2015) "I have sufficient resources to be able to donate money to conservation organizations to help reduce wildlife crime." (Han, 2015) "I have enough time to donate money to conservation organizations to help reduce wildlife crime." (Han, 2015) "I have enough opportunities to donate money to conservation organizations to help reduce wildlife crime." (Han, 2015) "Donating money to conservation organizations to help reduce wildlife crime is completely up to me." (Han, 2015; Ajzen, 2006) "If I donated money to conservation organizations, it would help them to reduce wildlife crime." (López-Mosquera et al., 2014) (1 = *Strongly disagree*, 7 = *Strongly agree*)	Modified to include the outcome behavior of donating money to reduce wildlife crime; and modified one item into three individual items on resources, time and opportunity. Ajzen, 2006; Han 2015; and López-Mosquera et al., 2014.
Intention	"I am willing to donate money to conservation organizations within the next month to help reduce wildlife crime." (Han 2015; Carfora et al., 2021) "I plan to donate money to conservation organizations within the next month to help reduce wildlife crime." (Han 2015; Carfora et al., 2021) "I will definitely donate money to conservation organizations within the next month to help reduce wildlife crime." (Carfora et al., 2021) (1 = *Strongly disagree*, 7 = *Strongly agree*)	Modified to include the outcome behavior of donating money to reduce wildlife crime and changed "over the next month" to "within the next month". Han, 2015 and Carfora et al., 2021

Value-Belief-Norm Measures

Table 7 indicates the items/scales used to measure the constructs of the value-belief-norm theory while also outlining the previous literature from which these measures were adapted and how they were modified to fit this dissertation given that this theory, too, has not previously been applied to examinations of this category of environmental behaviors.

Table 7 - Measures of value-belief-norm theory constructs

Construct	**Measures**	**References**
	How important are each of the following to you as guiding principles in your life? (1 = *Not at all important*, 7 = *Very important*)	
Biospheric values	"How important is it to you ---" • To prevent environmental pollution. • To protect the environment. • To respect nature. • To be in unity with nature.	All value items modified to be framed as a question instead of a statement like "It is important for him/her to…" Bouman et al., 2018
Altruistic values	"How important is it to you ---" • That every person has equal opportunities. • To take care of those who are worse off. • That every person is treated justly. • That there is no war or conflict. • To be helpful to others.	
Egoistic values	"How important is it to you ---" • To have control over others' actions. • To have authority over others. • To be influential. • To have money and possessions. • To work hard and be ambitious.	

Table 7 (cont'd)

Ecological worldviews	• "We are approaching the limit of the number of people the earth can support." • "Humans have the right to modify the natural environment to suit their needs." • "When humans interfere with nature, it often produces disastrous consequences." • "Human ingenuity will ensure that we do not make the earth unlivable." • "Humans are severely abusing the environment." • "The earth has plenty of natural resources if we just learn how to develop them." • "Plants and animals have as much right as humans to exist." • "The balance of nature is strong enough to cope with the impacts of modern industrial nations." • "Despite our special abilities, humans are still subject to the laws of nature." • "The so-called 'ecological crisis' facing humankind has been greatly exaggerated." • "The earth is like a spaceship with very limited room and resources." • "Humans were meant to rule over the rest of nature." • "The balance of nature is very delicate and easily upset." • "Humans will eventually learn enough about how nature works to be able to control it." • "If things continue on their present course, we will soon experience a major ecological catastrophe."	NEP scale; Dunlap, 2008 (1 = *Strongly disagree*, 7 = *Strongly agree*)
Awareness of consequences	"Wildlife crimes cause biodiversity loss, exhaustion of natural resources, and species extinction." "Wildlife crimes generate environmental impacts on the neighboring areas and wider environment." "Wildlife crimes such as illegal international trade in exotic species can cause the spread of infectious diseases from animals to humans." "Conservation organizations help to curb wildlife crime and mitigate its impacts." (Reverse coded) (1 = *Strongly disagree*, 7 = *Strongly agree*)	Modified to attribute the problem statement to wildlife crime and to mention relevant negative consequences of wildlife crime. Structure is from Han, 2015

Table 7 (cont'd)

Ascription of responsibility	"Every citizen must take responsibility for mitigating the environmental, economic, and health issues linked to wildlife crimes by donating money to conservation organizations." "The authorities are responsible for mitigating the environmental, economic, and health issues linked to wildlife crimes by financially supporting conservation organizations." "I am responsible for mitigating the environmental, economic, and health issues linked to wildlife crimes by donating money to conservation organizations." (1 = *Strongly disagree*, 7 = *Strongly agree*)	Modified to mention specific impact types of wildlife crime. Structure is from Carfora et al., 2021; and Gkargkavouzi et al., 2019. Both cited references use these items
Personal norms	"I feel I ought to donate money to conservation organizations to help reduce wildlife crime." "I would feel guilty if I did not donate money to conservation organizations to help reduce wildlife crime." "I feel morally obligated to donate money to conservation organizations to help reduce wildlife crime regardless of what others are doing." "I feel that donating money to conservation organizations to help reduce wildlife crime is the right thing to do." "I would feel good about myself if I donated money to conservation organizations to help reduce wildlife crime." (1 = *Strongly disagree*, 7 = *Strongly agree*)	Modified the action and outcome from López-Mosquera & Sánchez, 2012; Modified the action (donating money) and outcome (reducing wildlife crime) from Gkargkavouzi et al., 2019

Other Variables

This section outlines the scales and items used to measure wildlife value orientations (WVOs) (Dayer et al., 2007; Fulton et al., 1996; Vaske et al., 2022); as well as items measuring the dependent variable, and demographic variables.

Wildlife Value Orientations

As mentioned in Chapter 2, this dissertation is also an assessment of the suitability of wildlife value orientations as a valid and reliable measure of environmental behaviors specifically associated with wildlife conservation – such as donating money to conservation organizations to reduce wildlife crime. Given the criticism that the current measure of the ecological worldviews construct in the value-belief-norm model – the New Ecological Paradigm (NEP) – has received (Amburgey & Thoman, 2012), I used the measures outlined in Table 8, that have been developed and used widely for over a decade by scholars studying human dimensions of wildlife conservation.

A typology of beliefs about human-wildlife relationships such as domination (also known as utilitarianism) and mutualism is based on value dimensions. People who have a domination wildlife value orientation are more likely to believe that wildlife should be used and managed for human benefit, whereas those who have a mutualistic wildlife value orientation are likely to see wildlife as part of their extended family and as deserving of care and rights equal to what humans receive (Jacobs et al., 2018b; Manfredo, Teel, Carlos, et al., 2020; Teel et al., 2007b).

Table 8 - Measures of wildlife value orientations

	Domination Value Orientations
Appropriate use belief dimension (1 = *Strongly disagree* to 7 = *Strongly agree*)	"Humans should manage fish and wildlife populations so that humans benefit."
	"The needs of humans should take priority over fish and wildlife protection."
	"It is acceptable for people to kill wildlife if they think it poses a threat to their life."
	"It is acceptable for people to kill wildlife if they think it poses a threat to their property."
	"Fish and wildlife are on earth primarily for people to use."
Hunting belief dimension (1 = *Strongly disagree* to 7 = *Strongly agree*)	"We should strive for a world where there's an abundance of fish and wildlife for hunting and fishing."
	"Hunting is cruel and inhumane to the animals." (R)
	"Hunting does not respect the lives of animals." (R)
	"People who want to hunt should be provided the opportunity to do so."
	Mutualism Value Orientation
Social affiliation belief dimension (1 = *Strongly disagree* to 7 = *Strongly agree*)	"We should strive for a world where humans and fish and wildlife can live side by side without fear."
	"I view all living things as part of one big family."
	"Animals should have rights similar to the rights of humans."
	"Wildlife are like my family and I want to protect them."
Caring belief dimension (1 = *Strongly disagree* to 7 = *Strongly agree*)	"I care about animals as much as I do other people."
	"It would be more rewarding to me to help animals rather than people."
	"I take great comfort in the relationships I have with animals."
	"I feel a strong emotional bond with animals."
	"I value the sense of companionship I receive from animals."

Demographic Variables

I also measured social-demographic variables such as age, gender, education, income, employment status and political ideology as these have been known to be associated with environmental behaviors (Kollmuss & Agyeman, 2002) and I expected them to relate to the dependent variable – intent to donate money. The questionnaire for Indian participants categorized income levels using the Government of India's income tax brackets to maintain a sense of uniformity and familiarity for participants rather than simply converting the corresponding U.S. Dollar amounts into Indian National Rupees. For specific demographic measures for U.S. and Indian questionnaires, see Appendix I.

Expected Outcomes

This section outlines the relationships I expected to see between constructs of the theory of planned behavior and the value-belief-norm theory, as well as inter-theory relationships that I expected to see based on what scholars have found in previous research. The hypotheses outlined in this section were all analyzed using correlations and regressions. However, I also used structural equation modeling (SEM) to explore and analyze multivariate relationships and find out how well the data from both India and U.S. surveys is represented in the structural models that are based on the conceptual models of both theories (see Figures 1 and 2).

Value-Belief-Norm Theory Hypotheses

H 1a. Biospheric values are positively associated with ecological worldviews.

H 1b. Altruistic values are positively associated with ecological worldviews.

H 1c. Egoistic values are negatively associated with ecological worldviews.

H 2. Ecological worldviews are positively associated with awareness of consequences.

H 3. Awareness of consequences is positively associated with ascription of responsibility.

H 4. Ascription of responsibility is positively associated with pro-environmental personal norms.

H 5. Pro-environmental personal norms are positively associated with donation intentions to reduce wildlife crime.

Theory of Planned Behavior Hypotheses

H 6. Attitudes towards monetary donation are positively associated with donation intentions to reduce wildlife crime.

H 7. Subjective norms are positively associated with donation intentions to reduce wildlife crime.

H 8. Perceived behavioral control is positively associated with donation intentions to reduce wildlife crime.

Other Expected Relationships

Based on the literature reviewed in Chapter 2, I also proposed the following hypotheses that relate concepts from the theory of planned behavior to concepts from the value-belief-norm theory. If supported, these hypotheses can help identify aspects of future conservation communication on wildlife crime reduction, and can contribute to theory testing and building, such as through the development of an integrated model that includes concepts from both theories and may have enhanced power to predict wildlife crime-related conservation behaviors.

H 9a. Awareness of consequences will be positively associated with attitudes towards donating money to reduce wildlife crime. (Han 2015; Carfora et al., 2021)

H 9b. Awareness of consequences will be positively associated with subjective norms. (Han, 2015)

H 9c. Awareness of consequences will be positively associated with perceived behavioral control. (Han, 2015)

H 10a. Ecological worldviews are positively associated with wildlife value orientations.

H 10b. Ecological worldviews are positively associated with attitudes towards donating money to reduce wildlife crime. (Carfora et al., 2021)

H 11a. Mutualistic wildlife value orientations will be positively associated with attitudes. (Teel et al., 2007b)

H 11b. Mutualistic wildlife value orientations will be positively associated with donation intentions to reduce wildlife crime. (Manfredo, Teel, Don Carlos, et al., 2020)

H 12. Biospheric values will be positively associated with mutualistic wildlife value orientations.(Oh et al., 2021)

H 13. Ascription of responsibility is positively associated with perceived behavioral control (Carfora et al., 2021).

Pilot Test and Rationale

I conducted pre-test interviews with five peers (doctoral students and friends) to test-run the questionnaire and identify potential issues with order effects, understandability, etc. (Collins, 2003; Haeger et al., 2012). After revising minor issues related to item wording or phrasing that were revealed during interviews, I launched a pilot test of the survey questionnaire on a small subset of respondents from India (n = 98) and the United States (n = 100). The pilot test was hosted online using the Qualtrics platform, which is also how participants were recruited. The pilot test helped identify potential issues with the online survey design, the Qualtrics flow, and setup, as well as potentially problematic response behavior from participants such as straight-lining, speeding, not paying attention, etc. Additionally, I was able to use results from the pilot test to determine whether I may have systematic issues with missing data due to incomplete responses etc.

In both India and U.S. samples, I observed straight-lining and speeding behavior but any missing data appeared to be rare and random rather than systematic, suggesting that the survey questions and response options were clear to participants. Any responses in which participants failed one or both attention checks in the questionnaire were automatically removed from the final list of “good completes” that Qualtrics provided. This likely helped minimize issues with missing and unreliable data quite substantially. Based on the pilot test, I included a speeding check for the final study such that respondents who completed the survey in less than 10 minutes would not be included in the final data as “good completes.” I also asked Qualtrics to add straight-lining behavior to their data scrubbing and cleaning criteria – which is part of their protocol before survey responses to the researcher after data collection. Finally, in both the pilot test and the final study, the order of questions within blocks was randomized. Items serving as measures of one common construct were considered to be within the same organizational survey ‘block’ as a part of the Qualtrics design element.

Analysis and Main Test

Upon ensuring that there were no systematic patterns of missing data, I conducted tests of normality and multicollinearity by looking at distributions, histograms, standard deviations, skewness, and kurtosis. I also tested for multicollinearity by examining Variance Inflation Factor (VIF) values. All the values for these tests were within acceptable limits; for example, VIF values did not exceed 5 for any variables, suggesting low to moderate correlations between variables. Additionally, I also conducted the Kaiser-Meyer-Olkin (KMO) test and the Bartlett’s test of sphericity to determine the factorability of the data. All KMO values were higher than 0.6 and all Bartlett's sphericity tests were significant at $p \leq 0.05$.

For the statistical analysis, I used SPSS to examine descriptives such as means, SDs, frequencies etc., and ran crosstabs and Chi-square tests. I also ran bivariate correlations, linear regressions, scale reliability, exploratory factor analyses with maximum likelihood estimation as the extraction method and promax rotations (Miller - Carpenter, 2018).

Finally, I conducted confirmatory factor analysis (CFA), multivariate normality tests, measurement invariance analysis, and ran structural equation models (SEM) using the lavaan, semTools, semPlot, equaltestMI, MVN, and tidyverse packages in R. Confirmatory factor analyses (CFA) are used to run measurement models which determine the relationships between indicators and the latent factors that they are said to measure, whereas the structural models are used to demonstrate relationships between different latent factors. While running the CFAs, I also examined the correlation matrices within the data, and calculated the Average Variance Extracted (AVE) to assess convergent and discriminant validity. To assess the fit of the measurement models (CFA) and structural models, I assessed different indices and measures of model fit such as Chi-square, Chi-square and degrees of freedom ratio, Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), the root mean square error of approximation (RMSEA), and the standardized root mean square residual (SRMR), while also examining factor loadings and retaining only those indicators (i.e., items) that had loadings greater than 0.5 on their respective latent factors (Carfora et al., 2021; Gkargkavouzi et al., 2019; van Riper & Kyle, 2014a).

CHAPTER FOUR: RESULTS

In conducting the confirmatory factor analyses and structural equation modelling, I found that different measurement and structural models would necessitate a parallel country-specific modelling approach. Therefore, any results presented to answer RQ1 will also help answer RQ2. To avoid redundancies, this chapter is organized by theory rather than by research question. The sections below, therefore, answer both RQ1 by identifying the social-psychological factors that mattered most in predicting donating intentions to curb wildlife crime, and RQ2 by highlighting cross-national differences in models and findings. A more detailed analysis of variable-specific cross-national differences in responses is available in Appendix J.

Exploratory Factor Analysis

This section outlines the protocol and rationale I followed for exploratory factor analysis (EFA) of latent factors in both theoretical models. Any theory-specific findings from the EFA are discussed in the theories' respective sections below.

First, I checked all the data for missing values. No more than five missing values were found in both countries' data, and no patterns of missing data emerged. On examining normality, I found that the standard deviations, histograms, skewness and kurtosis values indicate univariate normal distribution as none of the standard deviation (SD) values were greater than 2, none of the skewness values were greater than 3, and none of the kurtosis values were greater than 10 (X. Liu et al., 2018). To assess multicollinearity, I examined Variance Inflation Factor (VIF) values and on finding that none of them exceeded 5, I concluded that there were weak to moderate correlations between variables in the data, suggesting that multicollinearity was not a concern.

I conducted the Bartlett's test of sphericity and the Kaiser-Meyer-Olkin (KMO) test to validate whether the data from both countries were appropriate for running Exploratory Factor Analyses (EFA) on them. All variables met the criteria for suitability for proceeding with an EFA – i.e., KMO values were above 0.6 and Bartlett's tests were statistically significant for all variables (Miller - Carpenter, 2018; Obeng & Aguilar, 2018).

As I planned to conduct a Confirmatory Factor Analysis (CFA) first, and run structural equation models later on hypothesized conceptual models, I used maximum likelihood estimation as the extraction method for the EFA, and since I did expect the factors in both my theoretical models – TPB and VBN – to correlate with one another, I used the promax oblique rotation for EFAs. Items across both theories' sets of measures were retained only if they had factor loadings greater than 0.32 in the EFA, and greater than 0.5 in the CFA (Miller - Carpenter, 2018). I followed this procedure for the EFA for exploring factor loadings across constructs in both the theories – which I discuss individually next.

Value-Belief-Norm Theory

In determining the factorability of the data with respect to the latent factors in the value-belief-norm model (Stern et al., 1999), I followed the process for exploratory factor analysis outlined above. Values for the Kaiser-Meyer-Olkin (KMO) test were above 0.6 for all factors, with the lowest one being .65 for the 'ascription of responsibility' factor. Bartlett's tests of sphericity were also significant for all factor analyses. Items for most latent factors loaded on single-factor solutions representing those respective latent factors. However, 'egoistic values' and the 'NEP' items measuring ecological worldviews had multi-dimensional outputs. The five items for egoistic values loaded on two different factors in both samples, as demonstrated by the factor loadings, eigenvalues in the EFA output, and the scree plot. Similarly, the 15 items in the NEP scale loaded on three different factors in both samples as shown by their eigenvalues and scree plots. Further, values for the Variance Inflation Factor (VIF) did not exceed 3.8 when assessing multicollinearity, and while there were only rare instances of missing data that did not follow any patterns, I used the full information maximum likelihood estimation method for the SEM analysis involving this VBN model constructs.

I also assessed convergent validity by calculating the Cronbach's alpha and Average Variance Extracted (AVE) values for all latent constructs in the VBN model, and by examining factor loadings of all included items to ensure they were above 0.3 in the EFA and above 0.5 in the CFA (Cheung & Wang, 2017; Tabachnick & Fidell, 2007).

Table 9 shows the means, standard deviations, and Cronbach's alpha for the items and latent variables in the VBN model for both Indian and US samples. The Cronbach's alpha values indicate that these measures and scales were far more reliable and internally consistent for the U.S. sample than they were for the Indian sample.

Table 9 - Means, standard deviations, and reliability for value-belief-norm theory concepts

Variables/Measures	**INDIA**		**USA**	
	Mean	**S.D.**	**Mean**	**S.D.**
New Ecological Paradigm (NEP)	4.70	.5963	4.84	.8829
(Unidimensional - USA α = .814; India α = .624)**				
Environmental Concern: (USA α = .795; India α = .693)				
NEP3: When humans interfere with nature, it often produces disastrous consequences.^	6.04	1.202	5.54	1.311
NEP5: Humans are severely abusing the environment.^	6.08	1.205	5.66	1.411
NEP9: Despite our special abilities, humans are still subject to the laws of nature.^	5.81	1.234	5.92	1.152
NEP13: The balance of nature is very delicate and easily upset.^	5.41	1.456	5.38	1.438
NEP15: If things continue on their present course, we will soon experience a major ecological catastrophe.^	6.04	1.149	5.26	1.624

Table 9 (cont'd)

Anthropocentricism: (USA α = .761; India α = .701)				
NEP2: Humans have the right to modify the natural environment to suit their needs.	4.62	2.002	4.73	1.758
NEP8: The balance of nature is strong enough to cope with the impacts of modern industrial nations.	3.92	1.873	4.65	1.701
NEP10: The so-called 'ecological crisis' facing humankind has been greatly exaggerated.	3.38	1.838	4.65	1.899
NEP12: Humans were meant to rule over the rest of nature.	4.87	2.053	4.58	1.974
NEP14: Humans will eventually learn enough about how nature works to be able to control it.	2.92	1.599	4.49	1.755
Limits to Growth:				
NEP1: We are approaching the limit of the number of people the earth can support.~	5.32	1.493	4.41	1.745
NEP11: The earth is like a spaceship with very limited room and resources.~	5.02	1.867	4.61	1.803
Removed from analysis of both samples:				
NEP4: Human ingenuity will ensure that we do not make the earth unlivable.*	2.93	1.454	4.01	1.695
NEP6: The earth has plenty of natural resources if we just learn how to develop them.*	1.91	1.225	2.87	1.578
NEP7: Plants and animals have as much right as humans to exist.*	6.39	1.144	5.89	1.389
Awareness of Consequences (AC)	5.90	.8222	5.41	.9332
(USA α = .754; India α = .72)				
AC1: Wildlife crimes cause biodiversity loss, exhaustion of natural resources, and species extinction.	6.18	1.091	5.70	1.210
AC2: Wildlife crimes generate environmental impacts on areas in which they occur and on surrounding communities.	5.97	1.048	5.49	1.167
AC3: Wildlife crimes such as illegal international trade in exotic species causes the spread of deadly viruses and pathogens from animals to humans.	5.81	1.237	5.26	1.305
AC4: Conservation organizations help to curb wildlife crime and mitigate its impacts.	5.63	1.075	5.21	1.236
Ascription of Responsibility (AR)	5.97	.8605	4.66	1.325
(USA α = .783; India α = .685)				
AR1: Every citizen must take responsibility for mitigating the environmental, economic, and health issues linked to wildlife crimes by donating money to conservation organizations that work to address it.	6.18	.962	4.51	1.657

Table 9 (cont'd)

AR2: The authorities must take responsibility for mitigating the environmental, economic, and health issues linked to wildlife crimes by financially supporting conservation organizations that work to address it.	6.16	.973	5.18	1.442
AR3: I am responsible for mitigating the environmental, economic, and health issues linked to wildlife crimes by donating money to conservation organizations that work to address it.	5.57	1.322	4.29	1.653
Personal Norms (PN)	5.60	1.006	4.36	1.483
(USA α = .925; India α = .826)				
PN1: I feel I ought to donate money to conservation organizations to help reduce wildlife crime.	5.56	1.295	4.31	1.736
PN2: I would feel guilty if I did not donate money to conservation organizations to help reduce wildlife crime.	5.17	1.600	3.64	1.804
PN3: I feel morally obligated to donate money to conservation organizations to help reduce wildlife crime regardless of what others are doing.	5.38	1.362	3.89	1.784
PN4: I feel that donating money to conservation organizations to help reduce wildlife crime is the right thing to do.	5.88	1.136	4.99	1.507
PN5: I would feel good about myself if I donated money to conservation organizations to help reduce wildlife crime.	6.01	1.099	4.95	1.607
Biospheric Values (BioV)	6.55	.5948	5.54	1.130
(USA α = .869; India α = .794)				
BioV1: How important is it to you to prevent environmental pollution?	6.48	.882	5.5	1.379
BioV2: How important is it to you to protect the environment?	6.58	.701	5.59	1.317
BioV3: How important is it to you to respect nature?	6.66	.626	5.95	1.134
BioV4: How important is it to you to be in unity with nature?	6.46	.792	5.12	1.483
Altruistic Values (AltV)	6.11	.7045	5.76	.9269
(USA α = .803; India α = .673)				
AltV1: How important is it to you that every person has equal opportunities?	6.36	.887	5.93	1.207
AltV2: How important is it to you to take care of those who are worse off?	5.52	1.358	5.17	1.386
AltV3: How important is it to you that every person is treated justly?	6.11	1.124	6.09	1.101
AltV4: How important is it to you that there is no war or conflict?	6.29	1.029	5.85	1.302
AltV5: How important is it to you to be helpful to others?	6.25	.880	5.74	1.182

Table 9 (cont'd)

Egoistic Values (EgoV) (USA α = .758; India α = .678)**	5.16	.9489	3.80	1.138
EgoV1: How important is it to you to have control over others' actions?	4.34	1.822	2.62	1.727
EgoV2: How important is it to you to have authority over others?	4.09	1.839	2.51	1.640
EgoV3: How important is it to you to be influential?	5.36	1.336	3.95	1.793
EgoV4: How important is it to you to have money and possessions?*	5.70	1.221	4.53	1.602
EgoV5: How important is it to you to work hard and be ambitious?*	6.32	.887	5.40	1.432

* *Note: Items removed from reliability and SEM analysis due to poor EFA and CFA factor loadings*
~ *Note: NEP items excluded from analysis of reliability, CFA, SEM etc.*
^ *Note: NEP items measuring the environmental concern dimension.*
** *Note: Cronbach's alpha indicates reliability of scale including only retained items*

The Average Variance Extracted (AVE) for latent factors in the value-belief-norm model was not consistently good. Table 10 shows the AVE values for VBN constructs across both samples. As several factors did not have AVE values exceeding 0.5, these factors would not be considered to have convergent validity. This means that for those constructs in Table 10 that have AVE values below 0.5, the items or measures used do not do a good enough job of closely explaining the latent variable they were meant to measure (Cheung & Wang, 2017; My Easy Statistics, 2020; Tabachnick & Fidell, 2007).

Table 10 - Values of average variance extracted from VBN latent factors

Latent Variables in VBN	**Average Variance Extracted**	
	India	**USA**
Biospheric values	**.512**	**.625**
Altruistic values	.331	.439
Egoistic values	**.597**	**.546**
Environmental concern (NEP)	.257	**.701**
Anthropocentricism (NEP)	.326	.395
Awareness of consequences	.393	.45
Ascription of responsibility	.439	.488
Personal norms	.493	**.701**

Note: AVE values that are above the 0.5 cut threshold are in bold font.

Dimensionality of the New Ecological Paradigm Scale

Before getting to the results of the CFA and SEM, in this section I lay out the process I followed to be able to define my measurement models in the CFA accurately and in a manner that aligns closely with what previous literature on the value-belief-norm theory and the NEP scale suggests.

As I discuss in Chapter 2, the New Ecological Paradigm scale developed by Dunlap et al. (2000) has been used widely, including by those who developed the value-belief-norm theory (Stern et al., 1999; Stern & Dietz, 1994) as an operationalization of the theory's 'ecological worldviews' construct. A substantial number of studies in environmental psychology, environmental communication, and environmental behavior have used the NEP (Dunlap, 2008; Ntanos et al., 2019; Slimak & Dietz, 2006; Sparks et al., 2021; Tyllianakis & Ferrini, 2021) – and many have used is as a unidimensional scale that measures a single latent factor sometimes referred to as 'environmental concern' or just as ecological worldviews. Over the years, shorter versions of the original-revised 15-item scale have also been used (van Riper & Kyle, 2014a) but most studies using the NEP scale have only ever conducted exploratory factor analyses, if that, leaving much to be desired in terms of hard evidence of the factor structure of this larger construct.

One of the few scholars to not only conduct several CFAs on this scale, but to actually compare proposed measurement models of NEP, Amburgey & Thoman (2012) compared three different but commonly used approaches to conceptualizing and operationalizing the NEP. They found that the best model fit suggests that the NEP scale was in fact, a second-order latent factor with five correlated underlying dimensions, namely: balance of nature;

eco-crisis; anti-exemptionalism; limits to growth; and anti-anthropocentricism or human domination (Amburgey & Thoman, 2012).

In determining the factor structure for the NEP latent variable in my own data, therefore, I found through the EFA that all the items in the NEP scale loaded on three different factors and while some had poor loadings, others also cross-loaded on more than one factor. Comparing the items that loaded on my three EFA factors with the items loaded on to the five factors in the study by Amburgey & Thoman (2012), I determined that my data most closely resembled these three underlying factors of a second-order NEP: environmental concern (a combination of 'balance of nature' and 'eco-crisis' as explicated by Amburgey & Thoman (2012)), limits to growth, and anthropocentricism or human domination (a combination of the anti-exemptionalism and human domination dimensions explicated by Amburgey & Thoman (2012)).

I thereby began specifying my measurement model for the NEP CFA by investigating whether these three dimensions – environmental concern, limits to growth, and anthropomorphism – are contributing to a well-fitting model with high internal consistencies. I found that one of the two items measuring 'limits to growth' had extremely poor factor loadings across both US and Indian groups, necessitating its removal, and by extension, the exclusion of the single remaining item assessing that dimension as a minimum of two indicators are required for a CFA (Kenny, 2016). From the other two dimensions, some items showed poor loadings in one or both groups of respondents. I omitted these from the country-specific CFAs when specifying the measurement models.

Ultimately, when using the NEP latent variable in my larger value-belief-norm model assessments, I conceptualize, and therefore operationalize it as a second-order latent factor with two underlying dimensions – environmental concern and anthropomorphism – which is partly consistent with what Amburgey & Thoman (2012) found.

Confirmatory Factor Analysis

The VBN latent variables with low internal consistency (i.e., Cronbach's alpha below 0.7) for the Indian sample were: altruistic values; egoistic values; ascription of responsibility; and the unidimensional operationalization of the NEP scale measures (see Table 9). All latent factors had high reliability for the U.S. sample (i.e., greater than 0.7).

Given these inconsistencies in reliability across groups and latent factors, I aimed to answer some guiding questions with this CFA, namely: 1) Does the same measurement model fit data from both groups of respondents?; 2) Can relationships between latent factors in both groups be explained by the same structural model?; 3) How do measurement and structural model fits compare when the NEP scale latent factor is replaced by the mutualistic wildlife value orientations (WVOs) latent factor? Does the model with mutualistic wildlife value orientations have better predictive power than the original VBN model that includes the NEP scale as a measure of ecological worldviews?

To answer these guiding questions, I conducted a series of multi-group confirmatory factor analyses (MGCFA) to identify models that fit the data well, to identify cross-national differences between groups, and to test for measurement invariance or equivalence. All CFAs and MGCFAs included models that were specified based on an *a priori* theoretical model (see Figure 2). I used Rstudio (version 2022.02.3+492) to run all CFA, MGCFA, and SEM analyses, and to plot path diagrams. Specifically, I used the lavaan, haven, semTools, semPlot, equaltestMI, MVN, tidyverse, and magrittr packages in R. As established before, although I could establish univariate normality in the US sample for VBN variables and measures, some measures were not normally distributed within the India sample as evidenced by the higher standard deviations seen in Table 9.

I assessed multivariate normality using the MVN package. When looking at multivariate relationships simultaneously, both sets of data – the India and the U.S. data – did not exhibit normality as demonstrated by the Mardia skewness and kurtosis values (see Appendix A). However, the assumption of normality is a requirement of the method of estimation, namely, maximum likelihood, and not a requirement of the SEM analysis itself, and it is also worth keeping in mind that normality assumptions apply not to the exogenous independent variables, but the residuals, and therefore, only apply to endogenous variables. This is why I use the robust maximum likelihood estimation, and report the robust fit statistics and Satorra-Bentler Chi-square and standard error values for CFA and SEM models (CenterStat, 2019; Finney & DiStefano, 2006; Hoyle & Isherwood, 2013; Satorra & Bentler, 1994).

Testing the models for equivalence, my steps would involve running CFAs to examine one unrestricted measurement model in which the data were stacked overall without grouping by country; a second unrestricted model in which the stacked data were grouped by country; a third model in which factor loadings were made equal; a fourth model in which regression paths were constrained to be equal; and a fifth model in which both intercepts and factor loadings were constrained to be equal (Boomsma et al., 2012; Kenny, 2016, 2020; Pirralha, 2020b, 2020c, 2020a; Thakkar, 2020).

In following these steps and running the CFAs, I found that for the value-belief-norm model, as with the planned behavior model, I did not have even weak invariance – meaning that measurement models were different for both the Indian and U.S. groups. There were several problematic indicator items in the VBN data as evidenced both by the low scale reliability of many of the VBN factors in the Indian sample, and the lack of convergent validity for several VBN latent factors across both samples.

Primarily, the items with poor factor loadings in both EFAs and CFAs that were common to both groups were a handful of the NEP items (see Table 9), and two of the items measuring egoistic values. Specifically in the Indian sample, one of the measures for altruistic values, and additional measure of egoistic values, and a couple of the NEP items were excluded from the CFA and SEM analysis due to their poor factor loadings on all models. In the US sample, apart from one or two different NEP items that loaded poorly and were excluded from the analysis, I was able to retain most of the measures for other latent factors. This was not surprising as I could see that the data fit the US sample and distributions more normally than it did the Indian sample.

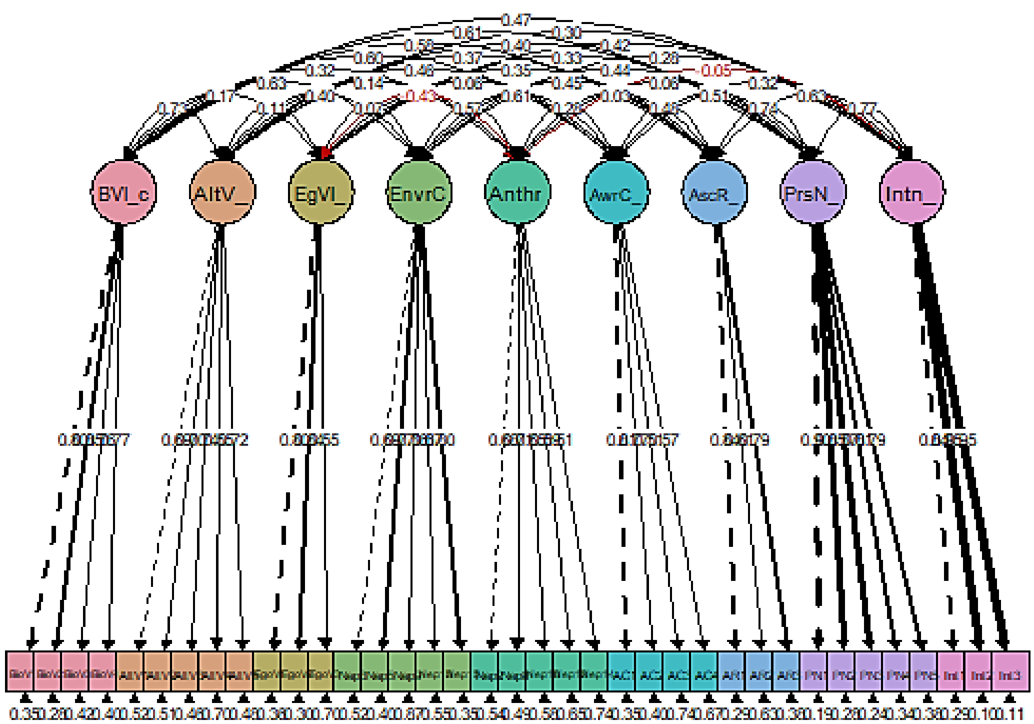

Figure 3 - Measurement model for original value-belief-norm model - USA

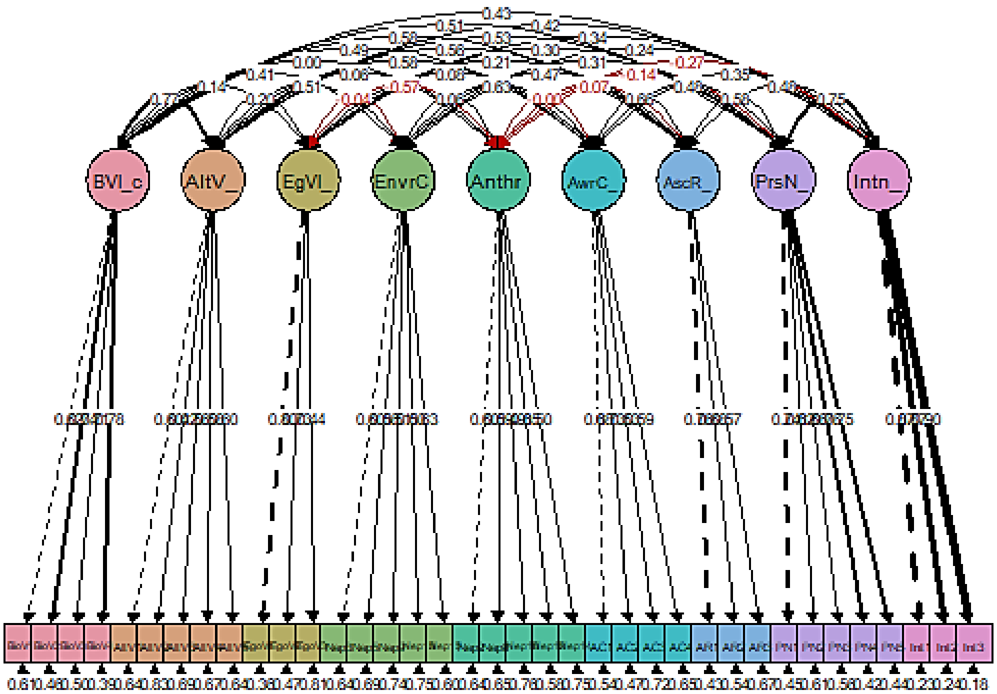

Figure 4 - Measurement model for original value-belief-norm model – India

Structural Equation Modeling

Given that the measurement models for both country groups appeared to be different (i.e., not 'invariant'), I followed a similar process to test the equivalence of structural models, again finding that even weak invariance could not be established. Here, I present the results of the SEM.

The fit statistics for the structural equation model that that best describes the ability of item measures to explain latent variables, and the relationships between these latent variables in the Indian sample data are: χ^2 = 1316.455, *df* = 561; *p* < .001; CFI = .925; TLI = .918; RMSEA = .042; SRMR = .077. Figure 5 shows this model.

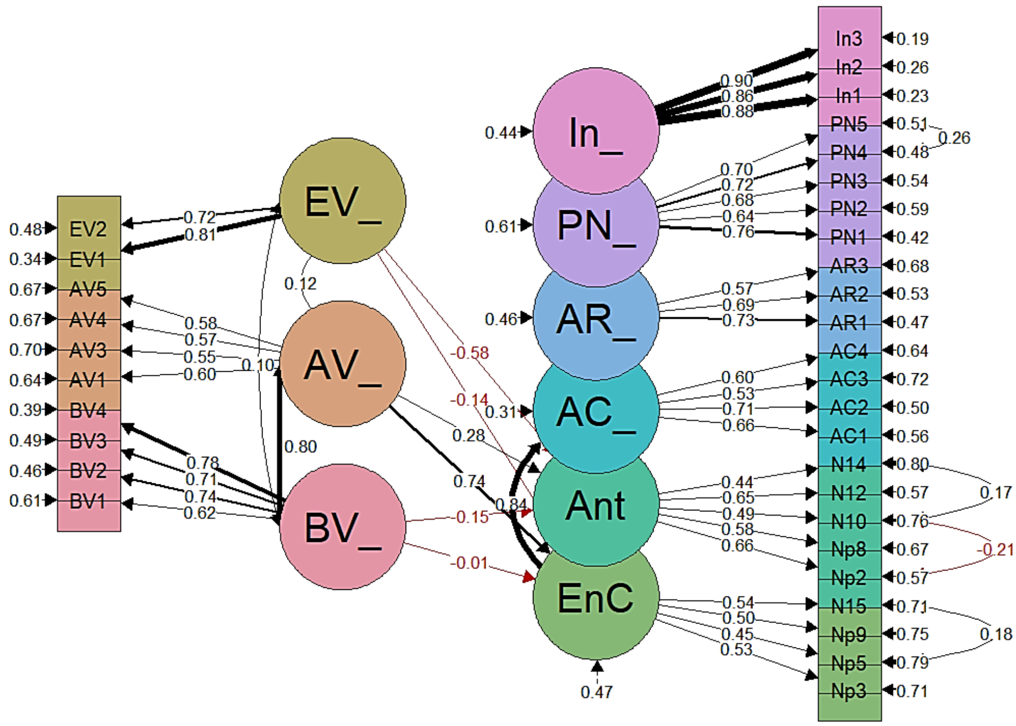

Figure 5 - Complete SEM and measurement model for value-belief-norm theory - India

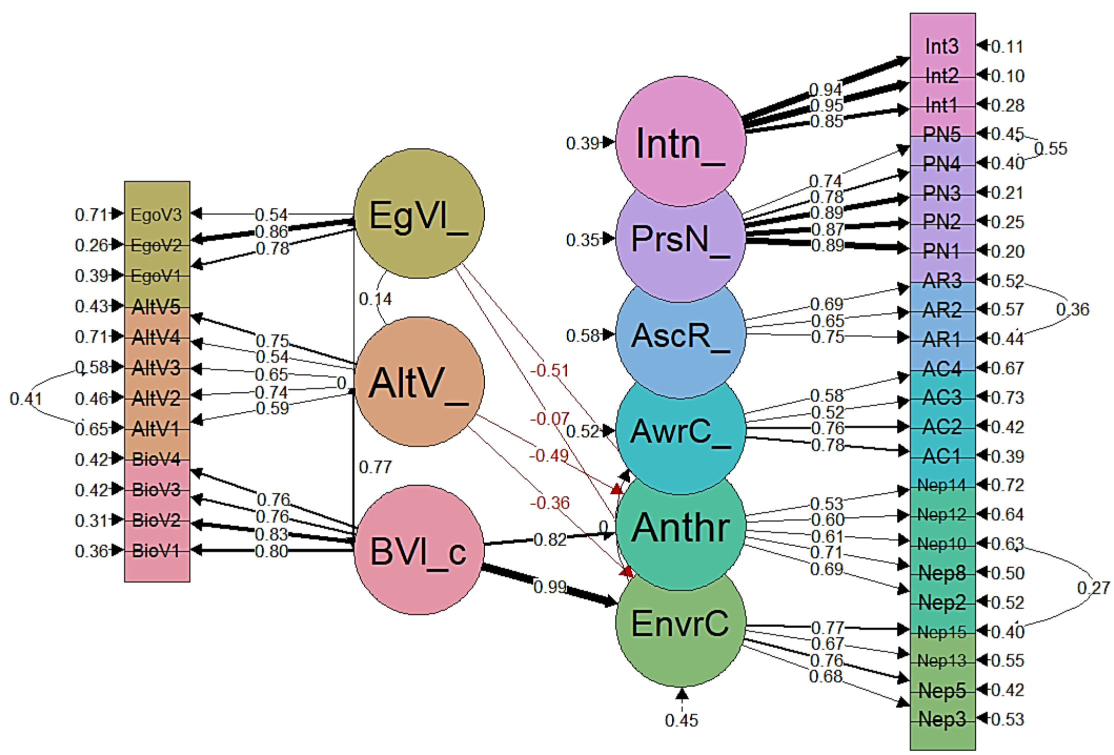

Figure 6 - Complete SEM and measurement model for value-belief-norm theory – USA

Figure 6 visually represents the structural equation and measurement models that fit the U.S. sample: χ^2 = 2214.262, df = 576; p < .001; CFI = .912; TLI = .903; RMSEA = .056; SRMR = .109.

Hypothesis Testing

Based on the SEM analysis, I present results of the proposed relationships between VBN constructs here (Stern et al., 1999; Stern & Dietz, 1994). I also include standardized regression coefficients for linear regressions to demonstrate how these coefficients change from a bivariate linear analysis to a multivariate structural equation modeling analysis. My assessment of whether these hypotheses are supported is based on the SEM results for both countries.

H1a. This hypothesis posits that biospheric values are positively associated with ecological worldviews. First, I ran correlations between biospheric values and the two underlying dimensions of the higher-order NEP latent variable – environmental concern and anthropocentricism. For US. respondents, biospheric values are positively and significantly associated with environmental concern (r = .551, p < .001) and with anthropocentricism (r = .259, p < .001). Among Indian respondents, while biospheric values were positively and significantly associated with environmental concern (r = .306, p < .001), their association with anthropocentricism was negative but non-significant. Linear regressions show that biospheric values predicted only 9.4% of the variance in environmental concern in Indian respondents [F (1, 918) = 94.807, p < .001; std. β = .306], but they predicted 30.4% of the variance in environmental concern among U.S. respondents [F (1, 898) = 392.251, p < .001; std. β = .551]. Multivariate regressions from the SEM show that biospheric values are negatively but non-significantly predictive of environmental concern among Indian respondents, however they significantly predicted environmental concern among U.S. respondents (std. β = .989, p < .001). Linear regressions examining the relationship between biospheric values and anthropocentricism show a small negative but non-significant association among Indian respondents but a small and significant association among U.S. respondents [F (1, 898) = 64.33, p < .001; std. β = .259]. Multivariate regressions from the SEM support this positive and significant relationship among U.S. respondents (std. β = .819, p < .001), and confirm no significant association for Indian respondents. Therefore, H1a is partially supported.

H1b. This hypothesis posits that altruistic values are positively related to ecological worldviews. For U.S. respondents, altruistic values are positively and significantly correlated with both environmental concern (r = .363, p < .001) and anthropocentricism (r = .106, p < .01). A linear regression shows that altruistic values explain 36.3% of the variance in environmental concerns among U.S. respondents [F (1, 898) = 136.290, p < .001; std. β = .363], and 10.6% of the variance in anthropocentricism [F (1, 898) = 10.134, p < .01; std. β = .106]. However, multivariate regressions from the SEM analysis show negative and significant relationships between altruistic values and both environmental concern (std. β = -.357, p < .001), and anthropocentricism (std. β = -.487, p < .001).

For Indian respondents, altruistic values are positively correlated with environmental concern (r = .333, p < .001) but non-significantly associated with anthropocentricism. A linear regression shows that altruistic values explain 33.3% of the variance in environmental concern in India [F (1, 918) = 114.332, p < .001; std. β = .333] and have no significant association with anthropocentricism. However, multivariate regressions from the SEM analysis show that altruistic values positively and, indeed, significantly predict both environmental concern (std. β = .741, p < .001) and anthropocentricism (std. β = .285, p < .01). Therefore, H1b is also partially supported given the unexpected negative associations found among U.S. respondents.

H1c. As per this hypothesis, egoistic values are negatively associated with ecological worldviews. For U.S. respondents, egoistic values positively correlated with environmental concern (r = .101, p < 0.01) and negatively with anthropocentricism (r = -.310, p < .001). A linear regression shows that egoistic values explained just about a percent of the variance in environmental concern [F (1, 898) = 9.242, p < .01; std. β = .10] and about 9.5% of the variance in anthropocentricism [F (1, 898) = 95.261, p < .001; std. β = -.31]. The multivariate SEM analysis shows that egoistic values negatively predict environmental concerns (std. β = -.07, p < .05) and anthropocentricism (std. β = -.513, p < .001).

For Indian respondents, egoistic values correlated negatively with anthropocentricism (r = -.376, p < .001) but non-significantly with environmental concern. Linear regressions show that egoistic values explain 37.6% of the variance in anthropocentricism [F (1, 918) = 151.323, p < .001; std. β = -.376] but had no significant predictive influence on environmental concern. However, these relationships were, in fact, significant in the SEM multivariate analysis. Egoistic values negatively predicted both environmental concern (std. β = -.142, p < .01) and anthropocentricism (std. β = -.58, p < .001). Therefore, based on the multivariate analyses, this hypothesis was supported.

H2. According to this hypothesis, ecological worldviews are posited to be positively associated with awareness to consequences. For U.S. respondents, both environmental concern (r = .489, p < .001) and anthropocentricism (r = .161, p < .001) were positively correlated with awareness of consequences. Linear regressions show that environmental concern and anthropocentricism explain 24.2% of the variance in awareness of consequences [F (2, 897) = 143.479, $p < .001$; std. β for environmental concern = .517, $p < .001$; std. β for anthropocentricism = -.064, $p < .05$]. Multivariate SEM analysis shows that environmental concern positively predicts awareness of consequences (std. $\beta = .723$, $p < .001$), but anthropocentricism negatively predicts awareness of consequences (std. $\beta = -.094$, $p < .05$).

For Indian respondents, environmental concern was positively correlated with awareness of consequences ($r = .452$, $p < .001$) but anthropocentricism does not significantly correlate with awareness of consequences. The linear regression shows that environmental concern and anthropocentricism explain 20.7% of the variance in awareness of consequences [F (2, 917) = 119.871, $p < .001$; std. β for environmental concern = .453, $p < .001$; std. β for anthropocentricism = -.05, p = not significant]. Again, in the multivariate analysis, both these relationships were significant such that environmental concern positively predicted awareness of consequences (std. $\beta = .84$, $p < .001$) whereas anthropocentricism negatively predicted awareness of consequences (std. $\beta = -.153$, $p < .001$). Therefore, based on the negative associations between anthropocentricism and awareness of consequences in both groups, this hypothesis is partially supported.

H3. This hypothesis posits that awareness of consequences is positively associated with ascription of responsibility. For U.S. respondents, awareness of consequences correlated positively with ascription of responsibility ($r = .453$, $p < .001$) and explained 20.5% of the variance in ascription of responsibility as seen in a linear regression [F (1, 898) = 232.022, $p < .001$; std. $\beta = .453$]. The multivariate SEM analysis shows that awareness of consequences strongly and positively predicted ascription of responsibility (std. $\beta = .651$, $p < .001$).

For Indian respondents also, awareness of consequences positively correlated with ascription of responsibility ($r = .464$, $p < .001$) and explained 21.6% of the variance in ascription of responsibility [$F(1, 918) = 252.407$, $p < .001$; std. $\beta = .464$]. As per the multivariate analysis, awareness of consequences strongly predicted ascription of responsibility (std. $\beta = .738$, $p < .001$). Therefore, based on the SEM analyses, H3 is supported.

H4. According to this hypothesis, ascription of responsibility is positively associated with personal norms. For U.S. respondents, ascription of responsibility correlated positively with personal norms ($r = .652$, $p < .001$) and explained 42.5% of the variance in personal norms [$F(1, 898) = 664.832$, $p < .001$; std. $\beta = .652$]. The SEM analysis shows that ascription of responsibility strongly and positively predicted personal norms (std. $\beta = .808$, $p < .001$).

Among Indian respondents also, ascription of responsibility was positively correlated with personal norms ($r = .443$, $p < .001$) and explained 19.6% of the variance in personal norms [$F(1, 918) = 224.330$, $p < .001$; std. $\beta = .443$]. The multivariate analysis shows that ascription of responsibility positively predicts personal norms (std. $\beta = .623$, $p < .001$). Therefore, this hypothesis is supported.

H5. This hypothesis suggests that personal norms will be positively associated with donation intentions to reduce wildlife crime. In the U.S. sample, personal norms positively and strongly correlate with donation intentions ($r = .73$, $p < .001$) and explained 53.2% of the variance in donation intentions [$F(1, 898) = 1021.899$, $p < .001$; std. $\beta = .73$]. The SEM analysis shows that personal norms strongly and positively predicted intentions to donate money to reduce wildlife crime (std. β = .779, p < .001).

For Indian respondents also, personal norms positively correlated with donation intentions (r = .644, p < .001) and explains 41.5% of the variance in donation intentions [F (1, 918) = 650.620, p < .001; std. β = .644]. The SEM analysis also shows that personal norms strongly and positively predicted intentions to donate money to reduce wildlife crime (std. β = .75, p < .001). Therefore, this hypothesis is also supported.

Table 11 and Table 13 provide a comparative assessment of the multivariate regression outputs for SEMs in which this original VBN model was tested across both countries.

Table 11 - Multivariate regressions testing the NEP-based value-belief-norm model in India

Relationship between predictor and outcome	Estimate	Std. Err.	z-value	Sig.	Std.all	Hypothesis supported
BioVal → EnvConcern	-0.017	0.148	-0.112	0.911	-0.011	H1a – Rejected
AltVal → EnvConcern	1.082	0.190	5.688	0.000	0.741	H1b – Supported
EgoVal → EnvConcern	-0.208	0.066	-3.161	0.002	-0.142	H1c – Supported
BioVal → Anthro	-0.191	0.117	-1.625	0.104	-0.154	H1a – Rejected
AltVal → Anthro	0.353	0.124	2.855	0.004	0.285	H1b – Supported
EgoVal → Anthro	-0.719	0.067	-10.752	0.000	-0.580	H1c – Supported
EnvConcern → AC	1.035	0.126	8.224	0.000	0.840	H2 – Supported
Anthro → AC	-0.222	0.061	-3.664	0.000	-0.153	H2 - Rejected
AC → AR	0.607	0.065	9.334	0.000	0.738	H3 – Supported
AR → PN	0.538	0.046	11.779	0.000	0.623	H4 – Supported
PN → Intention	0.885	0.057	15.590	0.000	0.750	H5 - Supported

BioVal, AltVal, EgoVal = Biospheric, Altruistic, and Egoistic values, respectively. EnvConcern = Environmental concern (NEP). Anthro = Anthropocentricism (NEP). AC = Awareness of consequences. AR = Ascription of responsibility. PN = Personal norms.

Table 12 - Std. covariances and correlated errors in the NEP-based VBN model in India

Relationship between predictor and outcome	Estimate	Std. Err.	z-value	Sig.	Std.all
PN4 ~~ PN5	0.161	0.027	5.928	0.000	0.262
Nep2 ~~ Nep10	-0.507	0.103	-4.926	0.000	-0.210
Nep10 ~~ Nep14	0.390	0.093	4.217	0.000	0.170
Nep5 ~~ Nep15	0.188	0.040	4.651	0.000	0.181
Biospheric values ~~ Altruistic values	0.805	0.026	30.852	0.000	0.805
Biospheric values ~~ Egoistic values	0.098	0.042	2.353	0.019	0.098
Altruistic values ~~ Egoistic values	0.117	0.046	2.549	0.011	0.117

Table 13 - Multivariate regressions testing the NEP-based value-belief-norm model in the USA

Relationship between predictor and outcome	Estimate	Std. Err.	z-value	Sig.	Std.all	Hypothesis supported
BioVal → EnvConcern	1.476	0.130	11.330	0.000	0.989	H1a – Supported
AltVal → EnvConcern	-0.533	0.105	-5.095	0.000	-0.357	H1b – Rejected
EgoVal → EnvConcern	-0.105	0.051	-2.070	0.038	-0.070	H1c – Supported
BioVal → Anthro	1.146	0.124	9.257	0.000	0.819	H1a – Supported
AltVal → Anthro	-0.681	0.112	-6.093	0.000	-0.487	H1b – Rejected
EgoVal → Anthro	-0.718	0.067	-10.682	0.000	-0.513	H1c – Supported
EnvConcern → AC	0.674	0.052	12.893	0.000	0.723	H2 – Supported
Anthro → AC	-0.094	0.038	-2.449	0.014	-0.094	H2 – Rejected
AC → AR	0.616	0.049	12.677	0.000	0.651	H3 – Supported
AR → PN	1.040	0.080	12.937	0.000	0.808	H4 – Supported
PN → Intention	0.734	0.046	15.800	0.000	0.779	H5 - Supported

BioVal, AltVal, EgoVal = Biospheric, Altruistic, and Egoistic values, respectively. EnvConcern = Environmental concern (NEP). Anthro = Anthropocentricism (NEP). AC = Awareness of consequences. AR = Ascription of responsibility. PN = Personal norms.

Table 14 - Std. covariances and correlated errors in the NEP-based VBN model in the USA

Relationship between predictor and outcome	Estimate	Std. Err.	z-value	Sig.	Std.all
PN4 ~~ PN5	0.558	0.044	12.762	0.000	0.548
AltV1 ~~ AltV3	0.335	0.035	9.562	0.000	0.412
AR1 ~~ AR3	0.470	0.072	6.507	0.000	0.356

Table 14 (cont'd)

Nep15 ~~ Nep10	0.410	0.062	6.650	0.000	0.273
Biospheric values ~~ Altruistic values	0.769	0.021	36.278	0.000	0.769
Biospheric values ~~ Egoistic values	0.165	0.038	4.294	0.000	0.165
Altruistic values ~~ Egoistic values	0.139	0.041	3.422	0.001	0.139

As pointed out in the previous section of this chapter, there were discrepancies not only in how the relationships between VBN latent factors manifested in the U.S. sample and the Indian sample, but also in how reliable and valid these commonly used VBN scales and measures seemed to be outside the United States. While the relationships between awareness of consequences, ascription of responsibility, and personal norms were expectedly positive and significant in both U.S. and Indian groups, these findings overall suggest that a cross-validation of commonly used measures and scales associated with the VBN model outside the United States, especially in developing economies, is crucial to establish reliability and validity of measures and, by extension, of results.

Theory of Planned Behavior

Exploratory factor analysis for TPB concepts revealed that all items measuring each individual latent factor loaded on their respective single-factor solutions, thereby suggesting strong convergence with the latent factor. Further, I assessed convergent validity by examining the Average Variance Extracted (AVE) which is calculated using the sum of the squared standardized factor loadings of items, and the number of items. AVE values for all TPB latent factors – attitudes, subjective norms, perceived behavioral control, and intention – were greater than 0.5 in both Indian and USA samples, suggesting that the item measures did closely explain their respective latent variables. In addition to the AVE values, I also ascertained convergent validity by assessing Cronbach's alpha for internal reliability (alpha for all scales was greater than 0.7), and only retained those items that had factor loadings higher than 0.32 in the EFA and higher than 0.50 in the CFA (Cheung & Wang, 2017; Miller - Carpenter, 2018). I also examined whether the value of the square root of the AVE values was greater than the correlations between latent variables to determine whether discriminant validity could be established. The only two latent variables for which the square root of AVE was not greater than latent variable correlations, were subjective norms and perceived behavioral control but this was the case only for the India dataset. While this suggests that subjective norms and perceived behavioral control measures may be slightly related to other measures instead of being sufficiently unrelated. However, the square root of AVE values for these latent variables only fell short of their correlations with other latent variables by values of 0.02 and 0.03, respectively, potentially suggesting that the technical lack of discriminant validity here may not be as severe.

Table 15 shows the means and standard deviations for the theory of planned behavior (TPB) concepts as seen in both India and the United States.

Table 15 - Means, standard deviations, and reliability for theory of planned behavior concepts

Variables and Measures	**USA**		**India**	
	Mean	**S.D.**	**Mean**	**S.D.**
Attitude (Att) (USA α = .957; India α = .905)	5.27	1.315	5.87	.965
Att1: I think the idea of donating money to conservation organizations to help reduce wildlife crime is very positive.	5.44	1.378	5.95	1.077
Att2: I think the idea of donating money to conservation organizations to help reduce wildlife crime is very responsible.	5.28	1.419	5.90	1.093

Table 15 (cont'd)

Att3: I think the idea of donating money to conservation organizations to help reduce wildlife crime is very intelligent.	5.15	1.443	5.66	1.253
Att4: I think the idea of donating money to conservation organizations to help reduce wildlife crime is very useful.	5.26	1.426	5.95	1.104
Att5: I think the idea of donating money to conservation organizations to help reduce wildlife crime is very ecologically helpful.	5.24	1.458	5.89	1.134
Subjective Norms (SN) (USA α = .884; India α = .809)	4.13	1.449	5.54	1.065
SN1: Most people who are important to me think that one should donate money to conservation organizations to help reduce wildlife crime.	4.13	1.597	5.56	1.231
SN2: Most people who are important to me expect that I will donate money to conservation organizations to help reduce wildlife crime.	3.77	1.713	5.40	1.346
SN3: Those people whose opinions I value would donate money to conservation organizations to help reduce wildlife crime.	4.47	1.509	5.68	1.176
Perceived Behavioral Control (PBC) (USA α = .828; India α = .864)	4.44	1.229	5.36	1.082
PBC1: I am confident that if I want, I can donate money to conservation organizations to help reduce wildlife crime.	4.75	1.684	5.65	1.285
PBC2: I have sufficient resources to be able to donate money to conservation organizations to help reduce wildlife crime.	3.29	1.910	4.98	1.616
PBC3: I have enough time to donate money to conservation organizations to help reduce wildlife crime.	4.24	1.717	5.17	1.475
PBC4: I have enough opportunities to donate money to conservation organizations to help reduce wildlife crime.	4.06	1.789	5.11	1.548
PBC5: Donating money to conservation organizations to help reduce wildlife crime is completely up to me.*	5.53	1.577	5.44	1.400
PBC6: If I donated money to conservation organizations, it would help them to reduce wildlife crime.	4.78	1.495	5.79	1.158

Table 15 (cont'd)

Intention (Int)	3.59	1.701	5.44	1.259
(USA α = .936; India α = 0.911)				
Int1: I am willing to donate money to conservation organizations within the next month to help reduce wildlife crime.	3.94	1.846	5.52	1.319
Int2: I plan to donate money to conservation organizations within the next month to help reduce wildlife crime.	3.49	1.788	5.41	1.353
Int3: I will definitely donate money to conservation organizations within the next month to help reduce wildlife crime.	3.35	1.787	5.38	1.428

* - *Item removed from reliability analysis and SEM due to poor factor loadings in EFA and CFA*

Confirmatory Factor Analysis

While measures used to assess the latent variables in the TPB model may have shown high reliability (Cronbach's alpha reported in Table 15), convergent validity, and for the most part, discriminant validity as well, it is important to recall that not only were these measures adapted to measure wildlife crime-related conservation behaviors from previous research on different kinds of environmental behaviors, but this is also the only study in which the theory of planned behavior has been applied to understand salient factors that may drive donation intentions to reduce wildlife crime. Given this two-fold contextual setting, I was interested in examining how well the different latent variables load onto their indicator items, and to identify the theoretical structures of these variables when applied to a new context and in a cross-national setting.

A confirmatory factor analysis (CFA) was performed to test an *a priori* defined conceptual model (see Figure 1) using both stacked cross-national data, and a multi-group confirmatory factor analysis (MGCFA) was also performed to test cross-national differences and assess measurement invariance or equivalence testing. Here too, I used R studio (version 2022.02.3+492) to run all CFA and structural equation modeling (SEM) analyses as well as to plot path diagrams. Again, I used the following packages with R: lavaan; haven; semTools; semPlot; equaltestMI; MVN; tidyverse; and magrittr.

As multivariate normality had already been assessed and I had established that the data did not have a normal multivariate distribution, I again used robust maximum likelihood estimation and reported robust fit statistics with Satorra-Bentler Chi-square and std. error values for the value-belief-norm CFAs and SEMs (CenterStat, 2019; Finney & DiStefano, 2006; Hoyle & Isherwood, 2013; Satorra & Bentler, 1994).

Additionally, although only a handful of questions had missing responses and no systematic pattern of missing data emerged, I used the full information maximum likelihood approach in conducting my CFAs and SEMs (Hoyle & Isherwood, 2013).

To examine whether the factor structure for the latent variables in the TPB model was the same across both countries, I applied the measurement invariance or equivalence testing steps (Boomsma et al., 2012; Pirralha, 2020a, 2020b, 2020c), beginning by looking at whether I could establish configural invariance in an unrestricted model in which factors were free to vary.

In running the configural invariance model for a multi-group CFA testing the measurement model of the theory of planned behavior, all indicator items except 'PBC5', an indicator of perceived behavioral control, were specified as measures of their respective latent variables (see Table 15); 'PBC5' was removed because it did not meet factor loading cut-offs during both the EFA and the CFA.

The MGCFA indicates that the measurement model fit the data well for both countries: Robust χ^2 = 878.601, df = 196, p < .001 (Robust χ^2 for India = 284.346; Robust χ^2 for USA = 594.256); Robust CFI = .954; Robust TLI = .943; Robust RMSEA = .077; SRMR = .062 (full model output in Appendix B). Figure 7 and Figure 8 visually depict the measurement models assessed in this multi-group CFA, showing how various indicators loaded on to their respective latent variables.

In testing equivalence, the next step was to add restrictions to this model, beginning with making item loadings on latent factors equal across both India and USA groups. While this restricted model was also a good fit for the data, a likelihood ratio test (LRT) meant for non-normal data – the scaled Chi-square difference test using the Satorra-Bentler method – was conducted to compare the unrestricted model with the restricted one found that both models were statistically significantly different such that weak invariance could not be established. This suggests that the measurement models for the theory of planned behavior are not similar across both the groups, meaning that values of factor loadings and latent means are likely not directly comparable across groups.

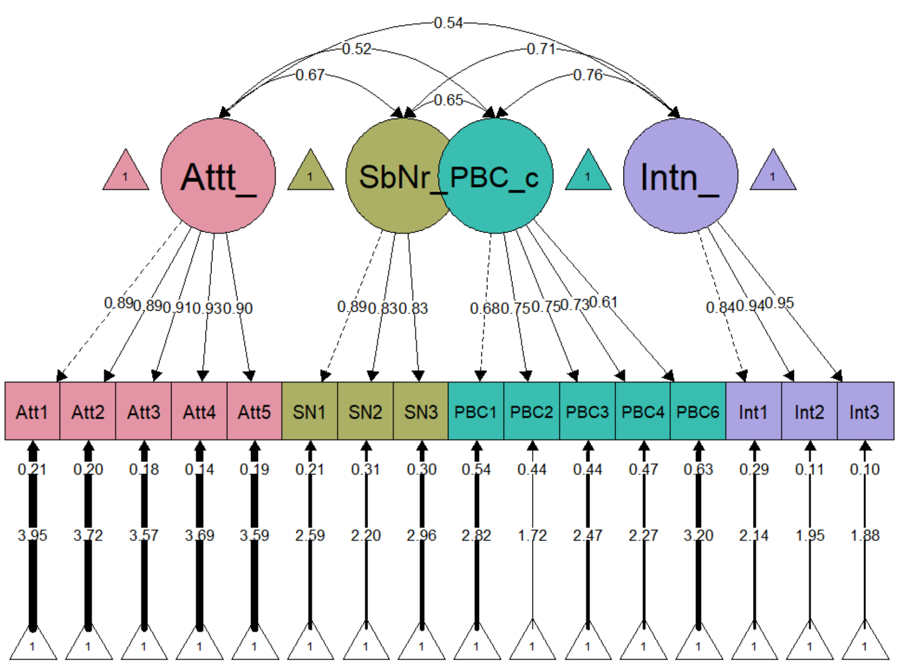

Figure 7 - Theory of planned behavior measurement model – USA

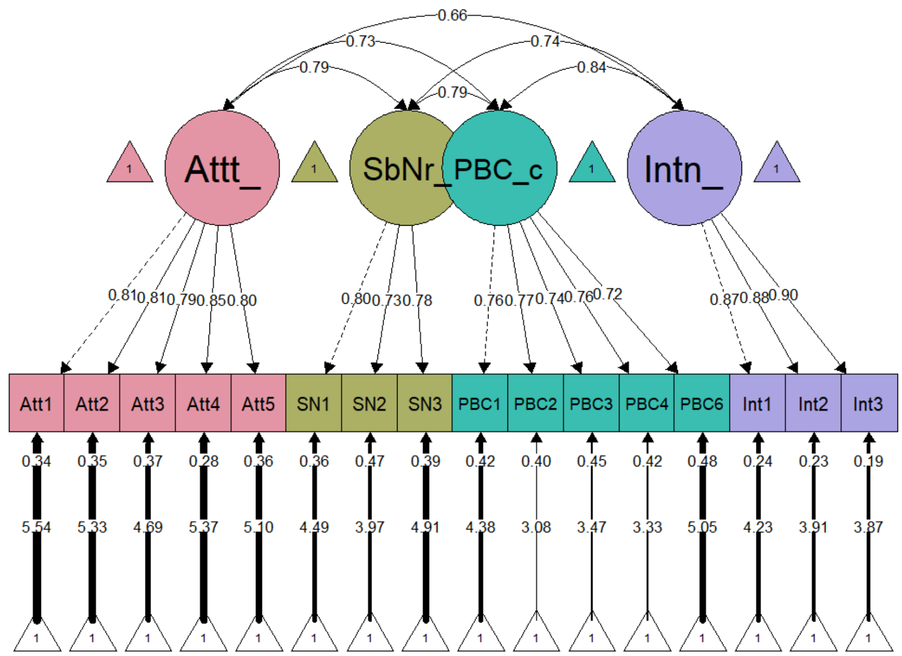

Figure 8 - Theory of planned behavior measurement model - India

Measurement models assessed in the MGCFA demonstrate how well the indicator items measure their latent variables, however, to examine relationships between the latent variables themselves, I used a structural equation model to examine whether it fit the data as well.

Structural Equation Model

Adding a regression to the above multi-group CFA model, I examined whether the theoretical factor structures – the relationships between latent factors – are the same across both groups. The SEM model was also tested for measurement invariance and since weak invariance could not be established, and it appeared that regression coefficients and factor loadings varied between countries, I conducted a parallel country models analysis. The SEM for India showed good model fit and explained 71.9% of the variance in intentions to donate for wildlife crime reduction: χ^2 = 443.524, *df* = 98, *p* < .001; CFI = .965; TLI = .958;

RMSEA = .062; SRMR = .039. The SEM for USA explained 66.2% of the variance in donation intentions to reduce wildlife crime: χ^2 = 912.975, *df* = 98, $p < .001$; CFI = .936; TLI = .921; RMSEA = .096; SRMR = .093. For full model output, see Appendix C.

Hypothesis Testing

Based on the SEM analysis, I present results of the proposed relationships between TPB constructs here (Ajzen, 1991).

H6. This hypothesis posited that attitudes towards monetary donation are positively associated with donation intentions to reduce wildlife crime. Correlational analysis showed that attitudes were positively and significantly related to donation intentions but that these correlations were moderate in both India (α = .599, $p = .01$) and the United States (α = .538, $p = .01$). A linear regression showed that attitudes significantly predicted 35.9% of the variance in donation intentions in India [F (1, 918) = 513.76, $p < .001$; std. $\beta = .599$] and 29% of the variance in donation intentions in the U.S. [F (1, 898) = 366.14, $p < .001$; std. β = .538]. However, examining multivariate regressions and relationships in the SEM model for the Indian sample shows that attitudes had no significant effect on donation intentions (std. $\beta = .016$, $p = .736$). Even in the USA sample, attitudes did not significantly predict donation intentions to reduce wildlife crime (std. $\beta = .029$, $p = .375$). Therefore, when examined as a part of multivariate relationships, attitudes were not significantly associated with donation intentions in both samples. H6, is therefore, not supported by the SEM evidence. I include the standardized beta coefficients of the linear regression and the multivariate SEM regression here because they are directly comparable, so assessing the difference between them can demonstrate how the standardized beta coefficient changed from a linear to multivariate analysis, in this case potentially indicating that the linear relationship between attitude and donation intentions may have been capturing some indirect effects given how much smaller the coefficients in the SEM analysis are.

H7. This hypothesis suggested that subjective norms are positively associated with donation intentions to reduce wildlife crime. Subjective norms were positively and significantly correlated with donation intentions in both India ($\alpha = .635$, $p < .001$) and the U.S. ($\alpha = .670$, $p < .001$). Linear regressions show that subjective norms predicted 40.3% of the variance in intentions in India [$F(1, 918) = 618.786$, $p < .001$; std. $\beta = .635$] and 44.9% of the variance in donation intentions the U.S. [$F(1, 898) = 731.271$, $p < .001$; std. $\beta = .67$]. When examining multivariate regressions and the SEM output, subjective norms moderately but significantly predicted donation intentions in the U.S. (std. $\beta = .36$, $p < .001$) and this effect was much smaller for the Indian sample (std. $\beta = .183$, $p < .01$). Here, too, comparisons between linear regression standardized beta coefficients and SEM multivariate regression beta coefficients shows that the linear regressions were likely accounting for some indirect effects as the coefficients reduced once examined as part of the SEM. Even so, both in bivariate and multivariate examinations, subjective norms were, indeed, positively associated with donation intentions to reduce wildlife crime in both samples, thereby, supporting H7.

H8. According to this hypothesis, perceived behavioral control would be positively associated with donation intentions to reduce wildlife crime. Perceived behavioral control and donation intentions were strongly and positively correlated in India ($\alpha = .743$, $p < .001$) and the U.S. ($\alpha = .664$, $p < .001$). Linear regressions showed that perceived behavioral control predicted 55.2% of the variance in donation intentions in India [$F(1, 918) = 1132.465$, $p < .001$; std. $\beta = .743$] and about 44% of the variance in donation intentions in the U.S. [F (1, 898) = 708.057, $p < .001$; std. $\beta = .664$]. The multivariate SEM analysis confirmed that perceived behavioral control strongly and positively predicted donation intentions to reduce wildlife crime in India (std. $\beta = .687$, $p < .001$), and in the U.S. (std. $\beta = .511$, $p < .001$). Comparing the standardized beta coefficients across linear and multivariate regressions assessing the influence of perceived behavioral control on donation intentions shows that most of the effect captured by the linear relationships across both samples continues to be captured in the multivariate analysis as well.

While not explicitly hypothesized, the theory of planned behavior also suggests that the three exogenous variables – attitudes, subjective norms, and perceived behavioral control – would be positively correlated with one another. The multivariate SEM model confirms these correlations; for instance, attitude and subjective norms were positively and strongly correlated (India: $r = .787$, $p < .001$; USA: $r = .671$, $p < .001$), as were attitude and perceived behavioral control (India: $r = .727$, $p < .001$; USA: $r = .524$, $p < .001$), and subjective norms and perceived behavioral control (India: $r = 789$, $p < .001$; USA: $r = .653$, $p < .001$).

Figure 9 and Figure 10 visually represent the structural model described above. As with the MGCFA model, equivalence testing found that weak invariance could not be established even for the SEM models for the theory of planned behavior. Therefore, the structural model also differed between groups as shown below.

Table 16 and Table 18 provide regression coefficients and other information from the SEM analyses for the U.S. and Indian samples, respectively, whereas Table 17 and Table 19 include the covariances for both samples.

Table 16 - Multivariate SEM regressions testing the theory of planned behavior in India

Relationship between predictor and outcome	Estimate	Std. Err.	z-value	Sig.	Std.all	Hypothesis supported
Attitude → Intention	0.027	0.088	0.302	0.763	0.014	H6 – Rejected
Subjective norm → Intention	0.316	0.112	2.829	0.005	0.168	H7 – Supported
Perceived behavioral control → Intention	1.317	0.118	11.171	0.000	0.698	H8 - Supported

Table 17 - Std. covariances in theory of planned behavior model in India

Relationship between predictor and outcome	Estimate	Std. Err.	z-value	Sig.	Std.all
Attitude ~~ Subjective Norms	0.787	0.019	42.214	0.000	0.787
Attitude ~~ Perceived behavioral control	0.728	0.020	36.397	0.000	0.728
Subjective norm ~~ Perceived behavioral control	0.788	0.020	40.313	0.000	0.788

Table 18 - Multivariate regressions testing the theory of planned behavior in the USA

Relationship between predictor and outcome	Estimate	Std. Err.	z-value	Sig.	Std.all	Hypothesis supported
Attitude → Intention	0.051	0.057	0.888	0.375	0.029	H6 – Supported
Subjective norm → Intention	0.619	0.074	8.362	0.000	0.360	H7 – Supported
Perceived behavioral control → Intention	0.879	0.074	11.948	0.000	0.511	H8 - Supported

Table 19 - Std. covariances in the theory of planned behavior model in the USA

Relationship between predictor and outcome	Estimate	Std. Err.	z-value	Sig.	Std.all
Attitude ~~ Subjective Norms	0.671	0.021	31.686	0.000	0.671
Attitude ~~ Perceived behavioral control	0.524	0.028	18.579	0.000	0.524
Subjective norm ~~ Perceived behavioral control	0.653	0.025	26.482	0.000	0.653

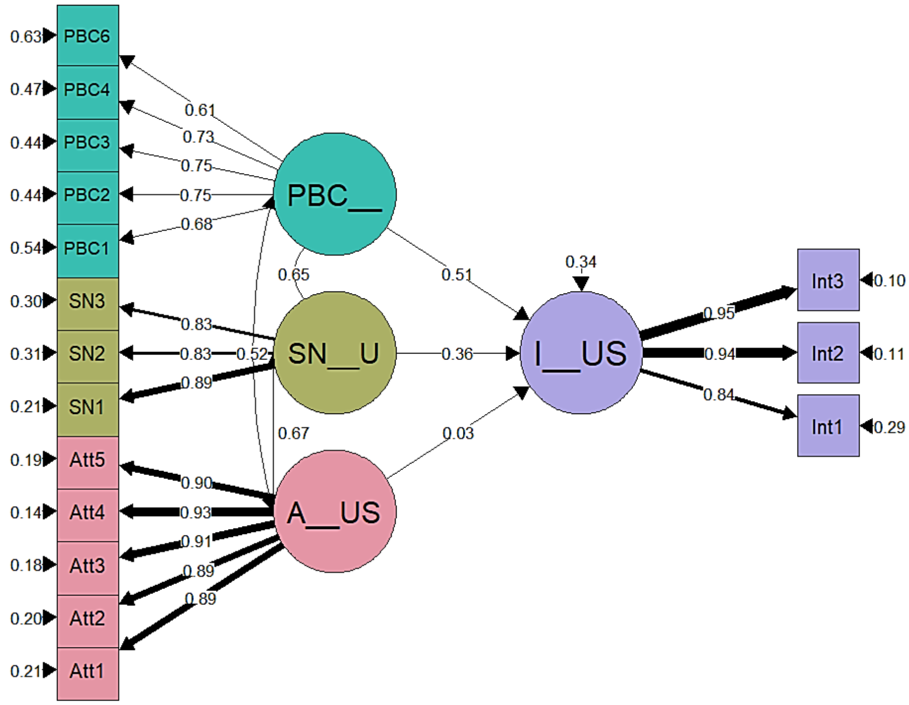

Figure 9 - Structural model of the theory of planned behavior - USA

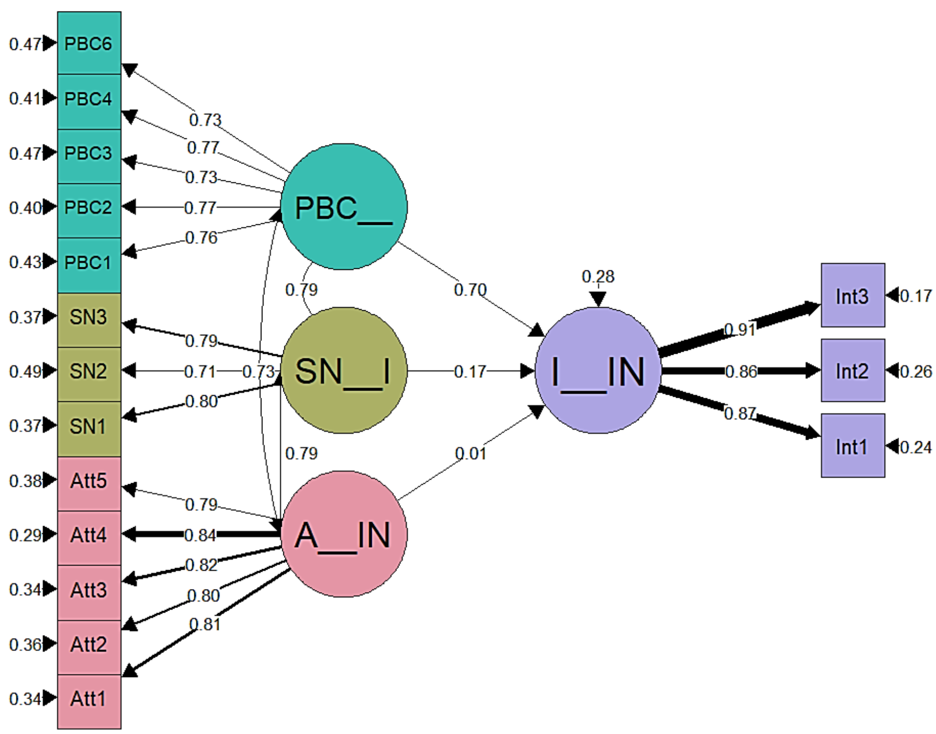

Figure 10 - Structural model of the theory of planned behavior - India

Other Hypotheses

In this section, I present results of some inter-theory relationships I hypothesized. These relationships were not subjected to CFAs or SEMs in models that combined constructs from the theory of planned behavior and the value-belief-norm theory. However, the correlations and linear regression results presented in this section can serve as precedent for future research that may be interested in developing integrated theoretical models. Other hypotheses focusing specifically on the wildlife value orientations construct are examined in the next section.

H9a. Awareness of consequences will be positively associated with attitudes towards donating money to reduce wildlife crime (Carfora et al., 2021; Han, 2015). A bivariate correlation analysis shows that awareness of consequences positively correlates with attitudes toward donation intentions in the U.S. sample ($r = .504$, $p < .001$) and in the Indian sample ($r = .403$, $p < .001$). Linear regressions show that awareness of consequences explained 25.4% of the variance in attitude in the U.S. [$F (1, 898) = 306.376$, $p < .001$; std. $\beta = .504$], and explained 16.3% of the variance in attitude in India [$F (1, 918) = 178.484$, $p < .001$; std. $\beta = .403$]. Thus, a positive association between these two variables suggests that this hypothesis is supported.

H9b. Awareness of consequences will be positively associated with subjective norms (Han, 2015). Positive correlations emerged both among U.S. respondents ($r = .416$, $p < .001$) and among Indian respondents ($r = .364$, $p < .001$). Awareness of consequences explained 17.3% of the variance in subjective norms in the U.S. [$F (1, 898) = 187.382$, $p < .001$; std. $\beta = .416$], and 13.3% of the variance in India [$F (1, 918) = 140.244$, $p < .001$; std. $\beta = .364$]. This hypothesis is, therefore, supported.

H9c. Awareness of consequences will be positively associated with perceived behavioral control (Han, 2015). Positive correlations were found among both U.S. respondents ($r = .344$, $p < .001$) and Indian respondents ($r = .35$, $p < .001$). Awareness of consequences explained 11.8% of the variance in perceived behavioral control among U.S. respondents [$F(1, 898) = 120.363$, $p < .001$; std. $\beta = .344$], and 12.3% of the variance in Indian responses [$F(1, 918) = 128.182$, $p < .001$; std. $\beta = .35$]. Findings suggest that these hypotheses are supported.

H10b. Ecological worldviews are positively associated with attitudes towards donating money to reduce wildlife crime (Carfora et al., 2021). Both environmental concern ($r = .404$, $p < .001$) and anthropocentricism ($r = .072$, $p < .05$) are positively correlated with attitudes for U.S. respondents, whereas for Indian respondents, only environmental concern is positively correlated with attitude ($r = .248$, $p < .001$) while anthropocentricism is negatively correlated with attitudes ($r = -.16$, $p < .001$). As ecological worldviews are conceptualized as preceding attitudes in the causal chain of variables explaining environmental behaviors, I ran a linear regression analysis which shows that environmental concern and anthropocentricism, together, explain 17.7% of the variance in attitude among U.S. respondents [$F(2, 897) = 96.4$, $p < .001$], but only about 9% of the variance in attitude among Indian respondents [$F(2, 917) = 44.033$, $p < .001$]. This hypothesis is supported based on the regression results.

H13. Ascription of responsibility is positively associated with perceived behavioral control (Carfora et al., 2021). Both for U.S. ($r = .478$, $p < .001$) and Indian respondents ($r = .426$, $p < .001$), ascription of responsibility was correlated positively with perceived behavioral control. In the U.S. sample, ascription of responsibility explains 22.8% of the variance in perceived behavioral control [$F (1, 898) = 265.357$, $p < .001$], while for the Indian sample, it explains about 18% of the variance in perceived behavioral control [$F (1, 918) = 203.189$, $p < .001$]. Therefore, this hypothesis is supported.

Wildlife Value Orientations in the Value-Belief-Norm Theory

As mentioned in Chapters 1 and 2, part of this dissertation involves assessing whether the wildlife value orientations construct could be an appropriate substitute for the NEP scale as an operationalization of the value-belief-norm theory's 'ecological worldviews' construct. In this section, I present the results of those hypotheses that involved examining the relationships between wildlife value orientations and some VBN constructs, as informed by an extensive review of interdisciplinary literature that sets the context for these hypotheses. I further present the results of a CFA conducted to assess the goodness of fit of a measurement model in which mutualistic wildlife value orientations replace the NEP scale as a measure of ecological worldviews, and the results of an SEM showing how the latent variables relate to one another in a model including mutualistic wildlife value orientations.

Hypothesis Testing

H10a. Ecological worldviews are positively associated with wildlife value orientations. More specifically, given that both these constructs are multi-dimensional latent factors, I expected environmental concern to be positively correlated with mutualistic wildlife value orientations but negatively correlated with domination wildlife value orientations. Conversely, I expected anthropocentricism to correlated positively with domination wildlife value orientations and negatively with mutualistic wildlife value orientations.

Among U.S. respondents, environmental concern correlated positively with mutualistic wildlife value orientations (r = .493, p < .001) and negatively with domination wildlife value orientations (r = -.376, p < .001). Among Indian respondents, environmental concern correlated positively with mutualistic wildlife value orientations (r = .401, p < .001) and negatively with domination wildlife value orientations (r = -.205, p < .001).

Anthropocentricism correlated negatively with domination wildlife value orientations (r = -.50, p < .001) and positively with mutualistic wildlife value orientations (r = .213, p < .001) for U.S. respondents. Among Indian respondents, anthropocentricism correlated negatively with both domination (r = -.528, p < .001) and mutualistic (r = -.088, p < .01) wildlife value orientations.

Given that both ecological worldviews and wildlife value orientations are sets of beliefs, I did not run regression analyses because I did not expect to eventually test a causal relationship between these factors. However, based on the mixed correlations, this hypothesis was only partially supported.

H11a. Mutualistic wildlife value orientations will be positively associated with attitudes (Teel et al., 2007b). Both for the U.S. (r = .460, p < .001) and Indian respondents (r = .537, p < .001), mutualistic wildlife value orientations were positively correlated with attitudes towards donating money to reduce wildlife crime. In fact, mutualistic wildlife value orientations explained 21.2% of the variance in attitudes among U.S. respondents [F (1, 898) =241.181, p < .001], and 28.8% of the variance in attitudes among Indian respondents [F (1, 918) = 371.054, p < .001]. On the other hand, and as expected, domination wildlife value orientations were negatively correlated with attitudes for both

U.S. (r = -.192, p < .001) and Indian (r = -.123, p < .001) respondents. This hypothesis, is therefore, supported.

H11b. Mutualistic wildlife value orientations will be positively associated with donation intentions to reduce wildlife crime (Manfredo, Teel, Don Carlos, et al., 2020). Both for U.S. (r = .425, p < .001) and Indian respondents (r = .491, p < .001), mutualistic wildlife value orientations correlated positively with intentions to donate money to reduce wildlife crime. For U.S. respondents, mutualistic wildlife value orientations explained 18% of the variance in donation intentions [F (1, 898) = 197.563, p < .001], whereas for Indian respondents, they explained about 24% of the variance in donation intentions [F (1, 918) = 291.067, p < .001]. This hypothesis is also, therefore, supported.

H12. Biospheric values will be positively associated with mutualistic wildlife value orientations (Oh et al., 2021). For both U.S. (r = .596, p < .001) and Indian respondents (r = .516, p < .001), biospheric values were positively correlated with mutualistic wildlife value orientations, and, as expected but not explicitly stated here, were negatively correlated with domination wildlife value orientations (U.S.: r = -.290, p < .001) (India: r = -.226, p < .001). Biospheric values explained 35.5% of the variance in mutualistic wildlife value orientations for U.S. respondents [F (1, 898) = 494.339, p < .001], and 26.6% of the variance for Indian respondents [F (1, 918) = 333.197, p < .001]. Further, results from the multivariate SEM analysis presented below show that biospheric values did, indeed, positively predict mutualistic wildlife value orientations in both U.S. (std. β = .817, p < .001) and Indian (std. β = .42, p < .001) groups, thereby supporting this hypothesis.

Measurement Model

Before running the confirmatory factor analysis, I conducted an EFA and ran the Bartlett's sphericity test along with the Kaiser-Meyer-Olkin test on items measuring mutualistic wildlife value orientations. KMO values were above 0.9 for both India and the U.S. group of respondents, and Bartlett's test of sphericity was significant in both groups as well. The EFA using maximum likelihood estimation for factor extraction and promax rotation showed that items loaded on a single-factor solution for both groups, and that factor loadings were greater than 0.5 for both groups as well. Moreover, a high Cronbach's alpha further underscored the reliability of these measures. For the Indian sample, Cronbach's α was .855 and for the U.S. sample, Cronbach's α was .902. The mutualistic wildlife value orientations construct, therefore, did not have the same problem with scale reliability that NEP measures did.

I conducted confirmatory factor analyses to determine the measurement model for mutualistic wildlife value orientations for both groups and found that model fit was better for the Indian sample [Robust χ^2 = 103.955, df = 27, p < .001, Robust CFI = .96, Robust TLI =.946, Robust RMSEA = .068, SRMR = .033] than it was for the U.S. sample which required re-specification after including correlated errors between items [Robust χ^2 = 228.489, df = 26, p < .001, Robust CFI = .927, Robust TLI =.898, Robust RMSEA = .117, SRMR = .047]. Figure 11 and Figure 12 depict the measurement model for mutualistic wildlife value orientations in the Indian and U.S. groups, respectively. For specific indicators used to measure this construct, see Table 8.

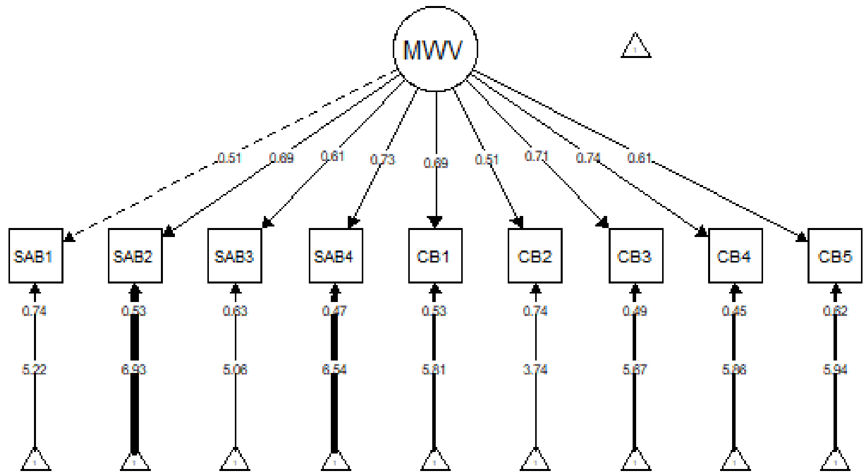

Figure 11 - Measurement model for mutualistic wildlife value orientations in India

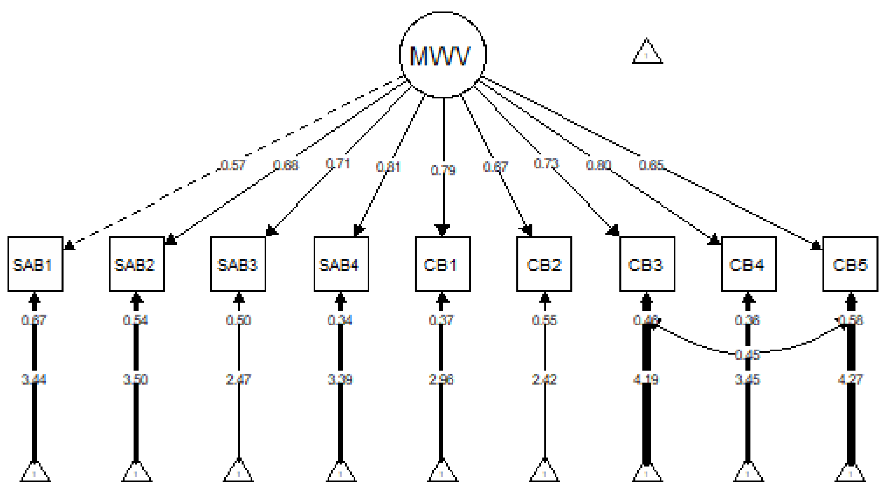

Figure 12 - Measurement model for mutualistic wildlife value orientations in the USA

While the model fit for the Indian sample was good without any correlated errors suggested by examining modification indices, this was not true for the U.S. measurement model which required at least one correlated error to be added to the model specification for the fit indices to be within acceptable ranges.

Structural Equation Model

To compare the path structure and predictive power of models in which the New Ecological Paradigm scale is replaced by mutualistic wildlife value orientations (WVOs) as part of the larger VBN model, I conducted an SEM analysis following the same protocols I used above, such as testing for measurement invariance and comparing equivalence.

I ran both CFAs and SEMs for the following models: 1) Overall stacked data without grouping by country and without constraints, 2) Stacked data with country-level grouping and without constraints (i.e., configural invariance), 3) Stacked data with country-level grouping and factor loadings constrained to being equal (i.e., metric invariance), and 4) Stacked data with country-level grouping and factor loadings and intercepts constrained to being equal (i.e., scalar invariance) (Pirralha, 2020a, 2020b, 2020c). I ran a likelihood ratio test in lavaan to compare model fit for testing equivalence.

I found that country-level differences mattered such that the grouped model had better fit and was significantly different from the overall stacked model without country-level grouping. This was consistent with the fact that the measurement model for mutualistic wildlife value orientations was itself different for the U.S. and India, as was the initial measurement model that tested the value-belief-norm model.

To compare whether the NEP-based VBN model or the Mutualistic WVO-based VBN model was the better fit for Indian and U.S. respondents, I looked at the model fit statistics and R^2 value since a likelihood ratio test that compares models can only be used when the models being compared are nested models.

For both groups, the model with mutualistic wildlife value orientations (WVOs) had slightly higher predictive power. For Indian respondents, though, the WVO-based VBN model had slightly better fit statistics and explained 56.5% of the variance in intentions to donate money to reduce wildlife crime [χ^2 = 1415.618, df = 515, p < .001, CFI = .928, TLI =.922, RMSEA = .044, SRMR = .069]. Figure 13 shows the structural model for the value-belief-norm theory with WVOs replacing NEP in India. Table 20 below shows the fit statistics and R^2 values for both value-belief-norm structural equation models as they apply to Indian respondents – the original one with NEP measures, and the one replacing NEP with mutualistic WVOs. Multivariate regressions and standardized covariances for these models are presented in Tables 22 through 25.

Table 20 - Fit statistics for value-belief-norm SEMs with NEP and WVOs for India

Model	Chi-square	df	AIC	BIC	CFI	TLI	RMSEA	SRMR	R^2
VBN_NEP	1321.9	509	91030	91609	.925	.918	.042	.07	.562
VBN_WVO	1415.618	515	83702	84252	.928	.922	.044	.069	.565

Table 21 - Fit statistics for value-belief-norm SEMs with NEP and WVOs for USA

Model	Chi-square	df	AIC	BIC	CFI	TLI	RMSEA	SRMR	R^2
VBN_NEP	2214.3	576	101868	102473	.912	.903	.056	.109	.608
VBN_WVO	2479.8	579	99206	99797	.907	.899	.06	.128	.612

For U.S. respondents, the fit statistics were better for the NEP-based VBN model. Table 21 provides fit statistics and R^2 values for both U.S. structural equation models testing the VBN models – the original one including NEP measures, and the one replacing NEP with mutualistic WVOs. Figure 14 shows the WVO-based VBN structural model for USA.

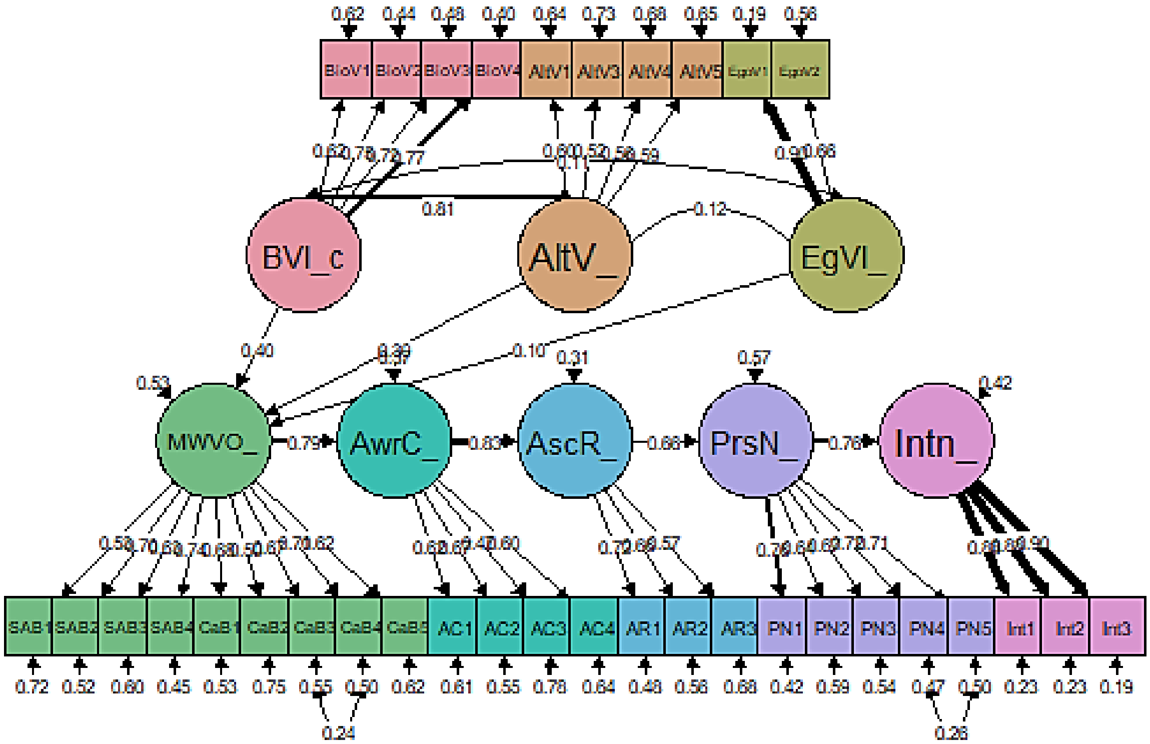

Figure 13 - Value-belief-norm SEM with mutualistic wildlife value orientations in India

First, I compared the multivariate regression outputs from the different structural equation models I ran to test the model fit and predictive power of a value-belief-norm model with mutualistic wildlife value orientations replacing the conventional NEP scale as a measure of ecological worldviews. Table 22 and Table 24 show how the relationships between latent factors in this model played out both in the U.S. and in India, and whether the proposed hypotheses were supported in either or both of these samples.

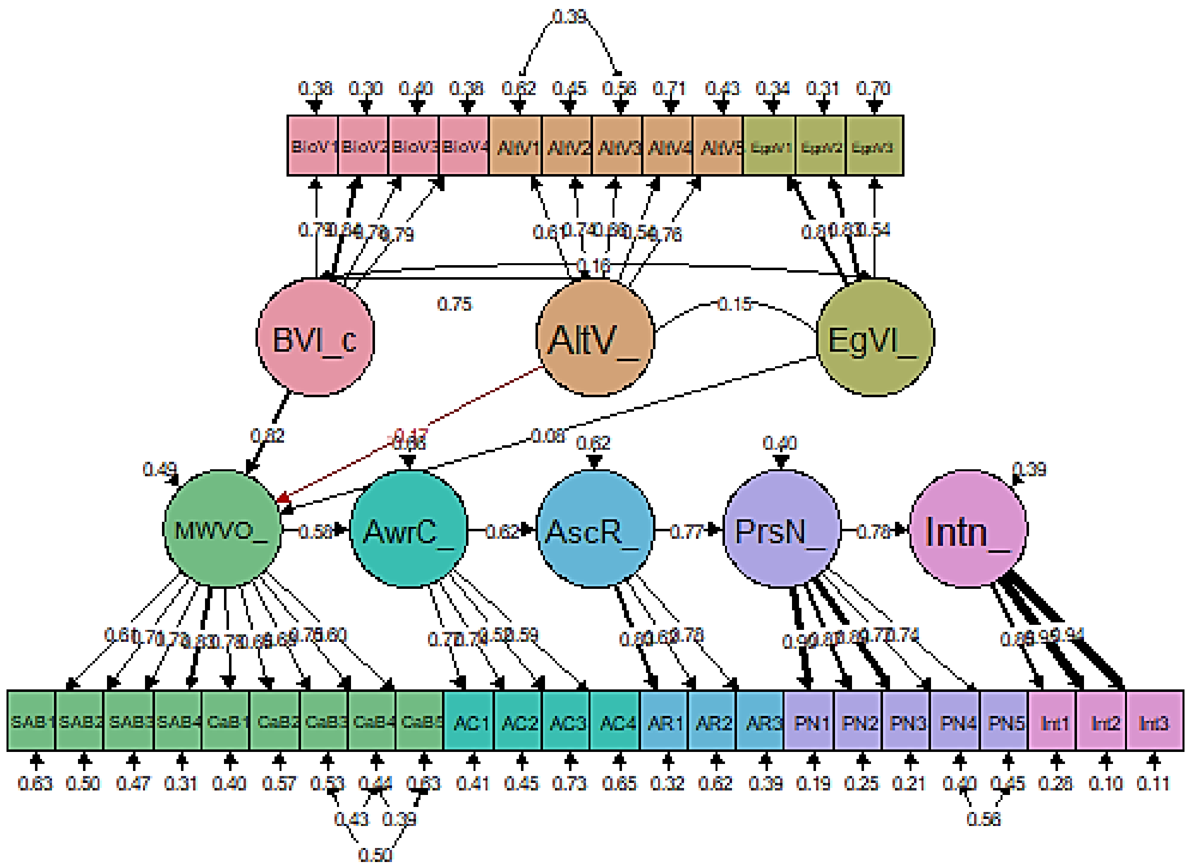

Figure 14 - Value-belief-norm SEM with mutualistic wildlife value orientations in the USA

Table 22 - Multivariate regressions testing the WVOs-based value-belief-norm model in the USA

Relationship between predictor and outcome	Estimate	Std. Err.	z-value	Sig.	Std.all	Hypothesis supported
BioVal → MutWVO	1.166	0.100	11.640	0.000	0.817	H1a - Supported
AltVal → MutWVO	-0.250	0.084	-2.991	0.003	-0.175	H1b – Rejected
EgoVal → MutWVO	0.116	0.045	2.558	0.011	0.081	H1c – Rejected
MutWVO → AC	0.496	0.038	13.032	0.000	0.578	H2 – Supported
AC → AR	0.639	0.049	13.168	0.000	0.617	H3 – Supported
AR → PN	0.954	0.061	15.750	0.000	0.771	H4 – Supported
PN → Intention	0.797	0.045	17.881	0.000	0.782	H5 - Supported

BioVal, AltVal, EgoVal = Biospheric, Altruistic, and Egoistic values, respectively. MutWVO = Mutual wildlife value orientations. AC = Awareness of consequences. AR = Ascription of responsibility. PN = Personal norms.

Table 23 - Std. covariances and correlated errors in the WVOs-based VBN model in the USA

Relationship between predictor and outcome	Estimate	Std. Err.	z-value	Sig.	Std.all
PN4 ~~ PN5	0.571	0.044	12.905	0.000	0.553
CaB3 ~~ CaB5	0.525	0.043	12.211	0.000	0.504
CaB3 ~~ CaB4	0.426	0.042	10.234	0.000	0.430
CaB4 ~~ CaB5	0.422	0.044	9.608	0.000	0.389
AltV1 ~~ AltV3	0.320	0.035	9.198	0.000	0.401
Biospheric values ~~ Altruistic values	0.746	0.022	33.700	0.000	0.746
Biospheric values ~~ Egoistic values	0.164	0.038	4.268	0.000	0.164
Altruistic values ~~ Egoistic values	0.152	0.041	3.742	0.000	0.152

Table 24 - Multivariate regressions testing the WVOs-based value-belief-norm model in India

Relationship between predictor and outcome	Estimate	Std. Err.	z-value	Sig.	Std.all	Hypothesis supported
BioVal → MutWVO	0.582	0.109	5.336	0.000	0.420	H1a – Supported
AltVal → MutWVO	0.397	0.115	3.440	0.001	0.287	H1b – Supported
EgoVal → MutWVO	0.133	0.046	2.907	0.004	0.096	H1c – Rejected
MutWVO → AC	0.940	0.069	13.722	0.000	0.793	H2 – Supported
AC → AR	0.923	0.093	9.935	0.000	0.835	H3 – Supported
AR → PN	0.483	0.046	10.578	0.000	0.659	H4 – Supported
PN → Intention	0.858	0.055	15.485	0.000	0.752	H5 - Supported

BioVal, AltVal, EgoVal = Biospheric, Altruistic, and Egoistic values, respectively. MutWVO = Mutual wildlife value orientations. AC = Awareness of consequences. AR = Ascription of responsibility. PN = Personal norms.

Table 25 - Std. covariances and correlated errors in the WVOs-based VBN model in India

Relationship between predictor and outcome	Estimate	Std. Err.	z-value	Sig.	Std.all
PN4 ~~ PN5	0.157	0.027	5.828	0.000	0.257
CaB3 ~~ CaB4	0.135	0.023	5.906	0.000	0.235
Biospheric values ~~ Altruistic values	0.806	0.026	30.946	0.000	0.806
Biospheric values ~~ Egoistic values	0.108	0.041	2.629	0.009	0.108
Altruistic values ~~ Egoistic values	0.122	0.045	2.701	0.007	0.122

As the tables above show, while most hypotheses were supported across both samples, altruistic values did not have a positive relationship with mutualistic wildlife value orientations in the U.S., whereas egoistic values did not have the expected negative relationships with the wildlife value orientations either. The absence of a negative association between egoistic value and mutualistic wildlife value orientations was also seen among Indian respondents. However, mutualistic wildlife value orientations had a much stronger association with awareness of consequences among Indian respondents than it did among U.S. respondents.

Relationships That Mattered Most – Graphical Representations

In conducting the SEM multivariate analysis, my objective was to assess how and to what extent the different latent variables in both the planned behavior and value-belief-norm models related to each other, and what, if any, differences there were in how these relationships manifested in samples from the two different countries. In this section, I present the graphical representations of the different structural models testing the two theories that fit the data for each country.

Value-Belief-Norm Model with NEP Dimensions

Figure 15 depicts the path model structure that fit the data to show relationships between the latent factors in the original value-belief-norm theory model with the two retained NEP dimensions for the U.S. sample. Figure 16 shows the relationships that emerged in the structural model for the India sample.

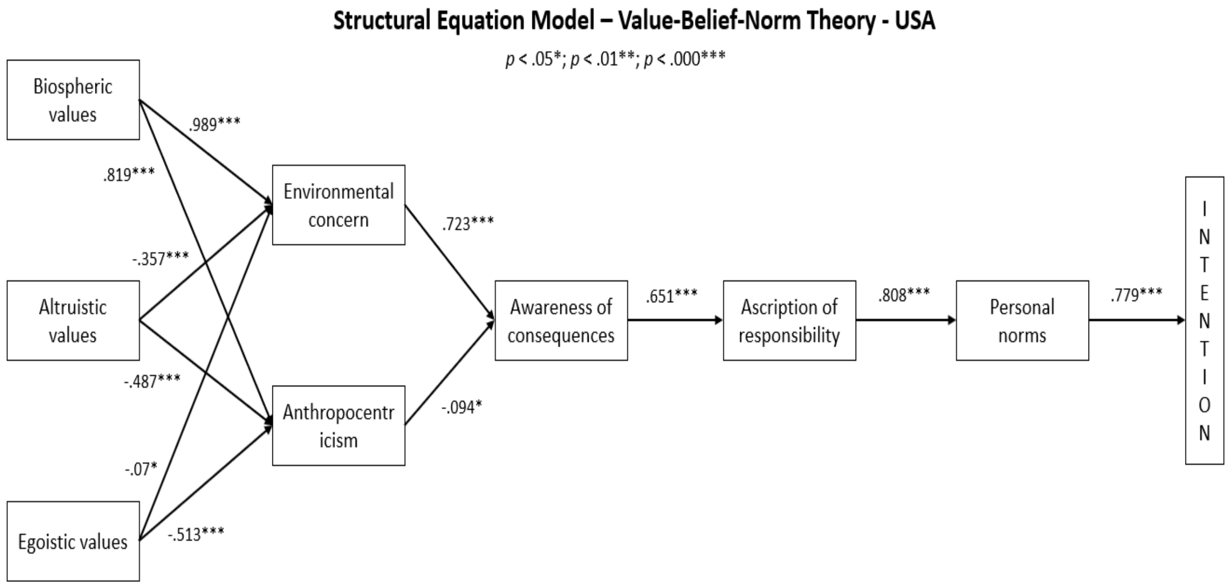

Figure 15 - Structural model of the value-belief-norm theory with only significant paths – USA

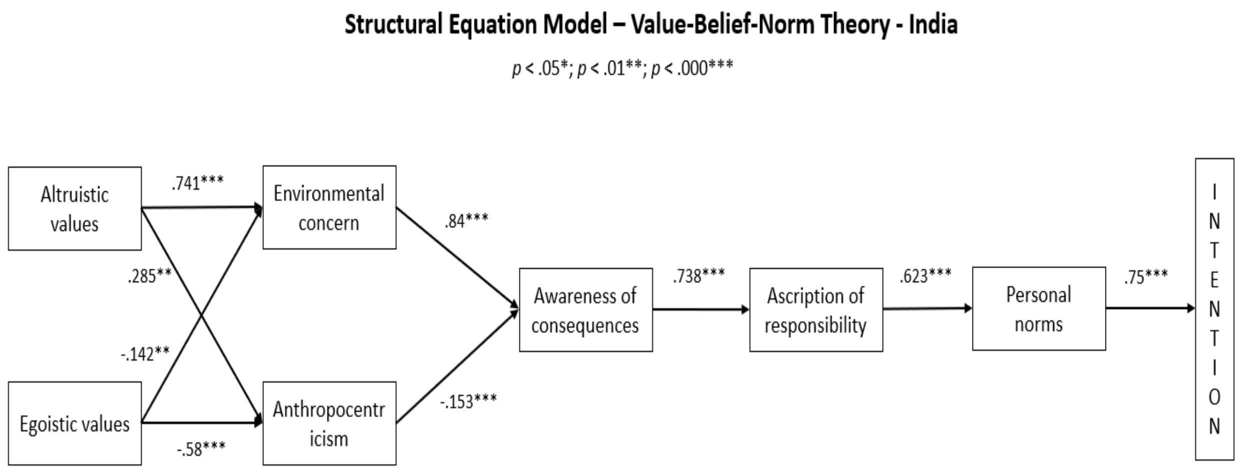

Figure 16 - Structural model of the value-belief-norm theory with only significant paths – India

Theory of Planned Behavior

Figure 17 depicts the path model structure that fits the data to show relationships between the latent factors in the theory of planned behavior model for the Indian sample while Figure 18 shows these relationships for the U.S. sample.

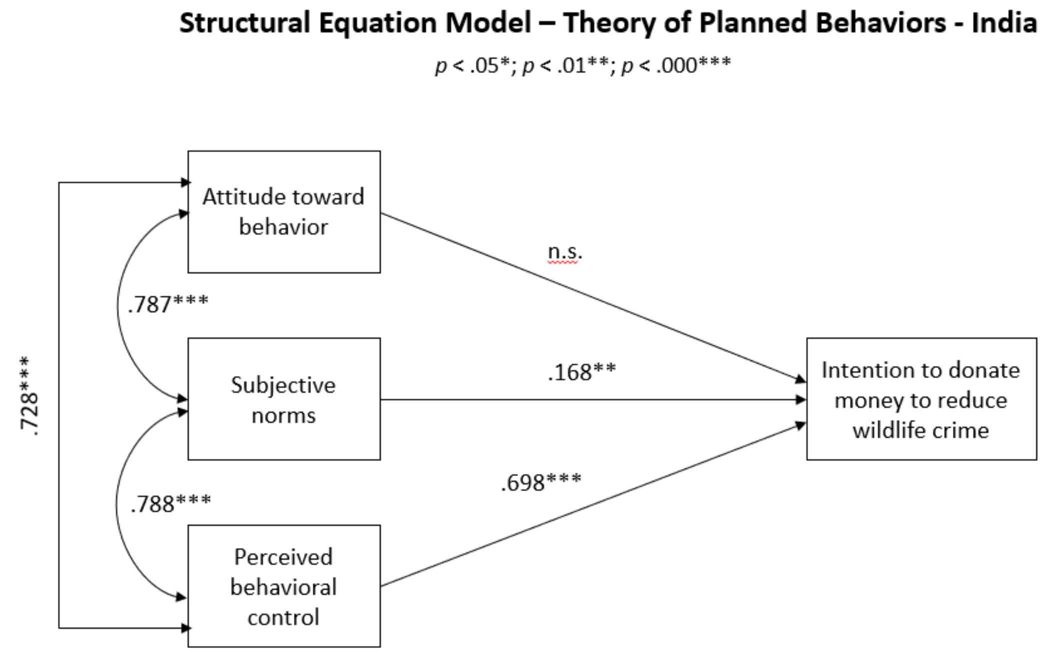

Figure 17 - Structural model of the theory of planned behavior with only significant paths – India

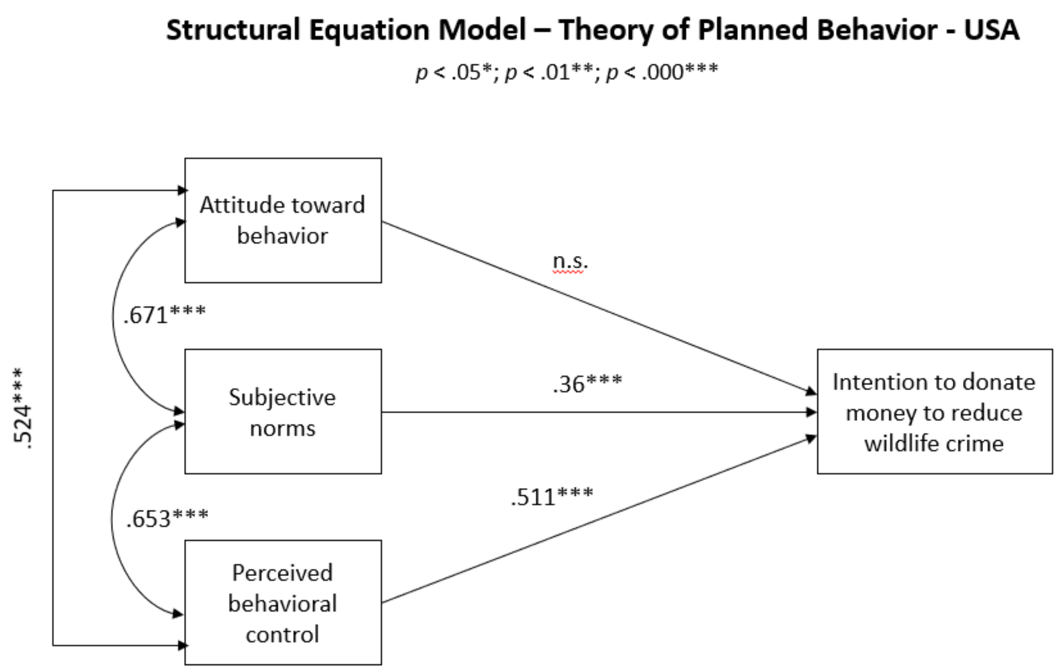

Figure 18 - Structural model of the theory of planned behavior with only significant paths - USA

Value-Belief-Norm Model with Wildlife Value Orientations

Figure 19 shows the structural path model for relationships between the latent factors in the modified value-belief-norm theory model with mutualistic wildlife value orientations replacing the NEP dimensions for the India sample whereas Figure 20 shows these relationships for the U.S. sample.

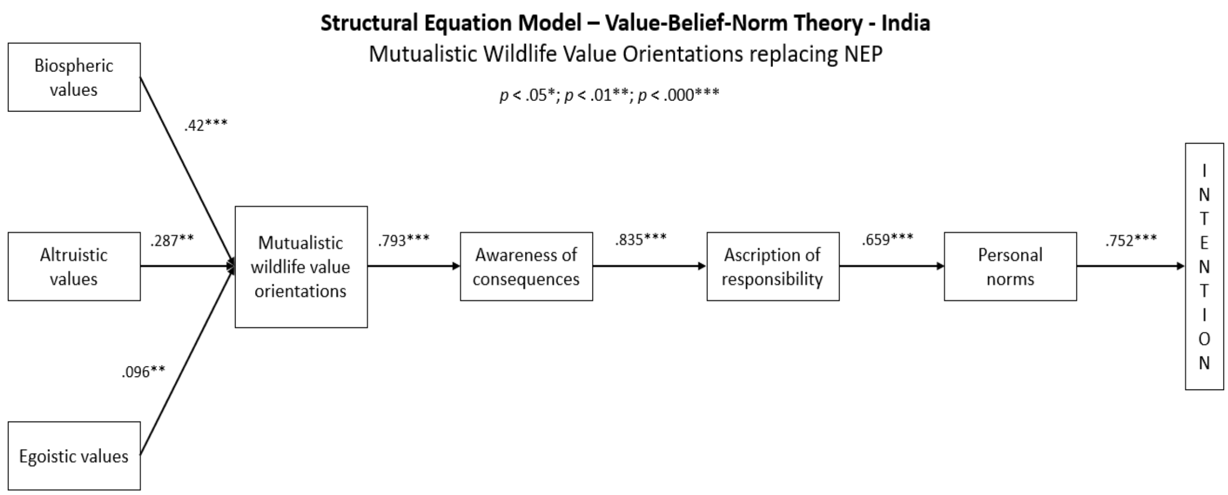

Figure 19 - Structural model with significant paths for the value-belief-norm theory with mutualistic wildlife value orientations - India

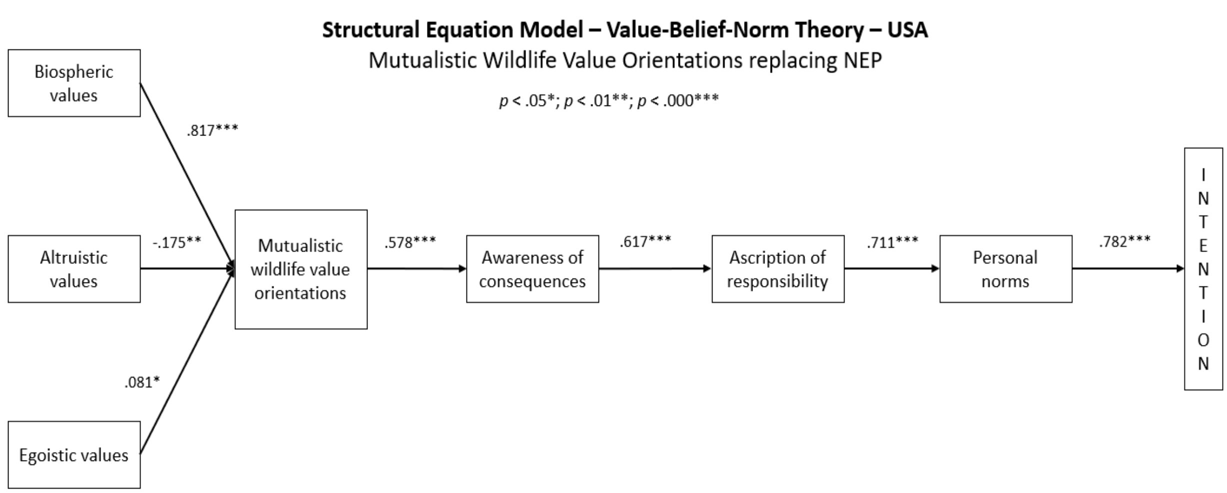

Figure 20 - Structural model with significant paths for the value-belief-norm theory with mutualistic wildlife value orientations – USA

Predictors That Mattered the Most

In the multivariate analysis, I was interested in identifying the factors that seemed to matter the most in predicting intentions to donate money to reduce wildlife crime. To examine this, I ran a multiple linear regression in SPSS to see which of the four direct predictors of intention – attitude towards the behavior, subjective norms, perceived behavioral control, and personal norms – had the highest regression coefficients cross-nationally in predicting donation intentions to reduce wildlife crime. I found that for Indian respondents, perceived behavioral control was most powerful, followed by subjective norms, personal norms, and attitudes, in that order. However, for U.S. respondents, personal norms were most powerful, followed by perceived behavioral control, subjective norms, and attitudes, in that order. Table 26 shows the results of this multiple linear regression comparison. Implications are discussed in the next chapter.

Table 26 - Multiple linear regression comparing salient drivers of donation intentions cross-nationally

Country		Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
			B	Std. Err.	Beta			Tolerance	VIF
0 USA	1	(Constant)	-.982	.165		-5.965	.000		
		Attitude	-.088	.041	-.068	-2.144	.032	.419	2.389
		Subjective norms	.259	.038	.221	6.755	.000	.399	2.509
		Personal norms	.474	.048	.413	9.973	.000	.248	4.032
		Perceived behavioral control	.430	.037	.311	11.474	.000	.580	1.723

Table 26 (cont'd)

1 India	1	(Constant)	-.231	.171		-1.353	.176		
		Attitude	.096	.042	.074	2.286	.022	.420	2.379
		Subjective norms	.201	.038	.170	5.343	.000	.429	2.333
		Personal norms	.168	.043	.134	3.955	.000	.376	2.656
		Perceived behavioral control	.568	.037	.489	15.306	.000	.427	2.342

a. Dependent Variable: Intention Intention to donate money to conservation organizations to help reduce wildlife crime

Broad Overview of Responses and Demographics

While testing the theory of planned behavior, although attitudes had no significant influence on predicting donation intentions to reduce wildlife crime in both India and the U.S., more respondents in both samples agreed with the attitudinal measures than those who disagreed. For instance, approximately 78% of U.S. respondents agreed on some level (from somewhat agree to strongly agree) with the statement that donating money to conservation organizations to help reduce wildlife crime is a positive thing, whereas nearly 91% of Indian respondents agreed with this statement on some level. Subjective norms appeared to be more meaningful among Indian respondents than among U.S. respondents. Considering responses to perceived behavioral control measures, the number of Indian respondents who strongly agreed with having sufficient resources to be able to donate money to conservation organizations for wildlife crime reduction was nearly three times the number of U.S. respondents who strongly agreed with the same statement. Conversely, the number of U.S. respondents who strongly disagreed that they had sufficient resources to donate to conservation organizations was 14 times the number of Indian participants who also strongly disagreed. However, when asking about resources, I wanted to be clear that I was not only asking about financial resources but was also interested in knowing whether time or the presence of opportunities to engage in such conservation behaviors are proving to be barriers for behavioral engagement in these groups, and if they are, what that would mean for those tasked with designing conservation campaigns and communications to reduce wildlife crime. More participants from India agreed that the recommended action – donating money to conservation organizations – would help in reducing wildlife crime than U.S. participants, who did not seem to agree quite as strongly as participants from India did.

Most of the participants who expressed strong intentions to donate money to conservation organizations to help reduce wildlife crime were from India. Responses to the other two items measuring donation intentions also aligned with this finding. For instance, of the number of participants who strongly agreed that they plan to donate money to conservation organizations within the next month to help reduce wildlife crime, n = 206 were from India while n = 56 were from the U.S, and of the number of participants who agreed with that statement, n = 299 were from India while n = 78 were from the U.S. Most participants from the U.S., in fact, either disagreed or strongly disagreed with the statement that they would definitely donate money to conservation organizations within the next month to help reduce wildlife crime. The implications of these findings are discussed in the next chapter.

From the value-belief-norm model, despite biospheric values not significantly predicting either of the two NEP dimensions in the India sample, they did significantly predict mutualistic wildlife value orientations, as expected, and were not one of the VBN constructs that had issues with convergent validity. While U.S. participants did also largely agree with biospheric value items, their responses were distributed between 'moderately important', 'very important', and 'extremely important', whereas most Indian participants rated all biospheric value items as either 'very' or 'extremely important'). While biospheric values fail to predict NEP dimensions among Indian participants, altruistic values played a significant role, and they also significantly and positively predict mutualistic wildlife value orientations among Indian respondents. Notably however, altruistic values failed to predict both dimensions of NEP – environmental concern and anthropocentricism – and mutualistic wildlife value orientations among U.S. respondents. It is immediately clear, however, that there are far more participants from India for whom having control over others' actions is important whereas for most respondents from the U.S., this is not that important. Further, across both groups combined, most participants who said it was either 'extremely important' or 'very important' to them to have control over others' actions, and to have authority over others were between 18 and 34 years old.

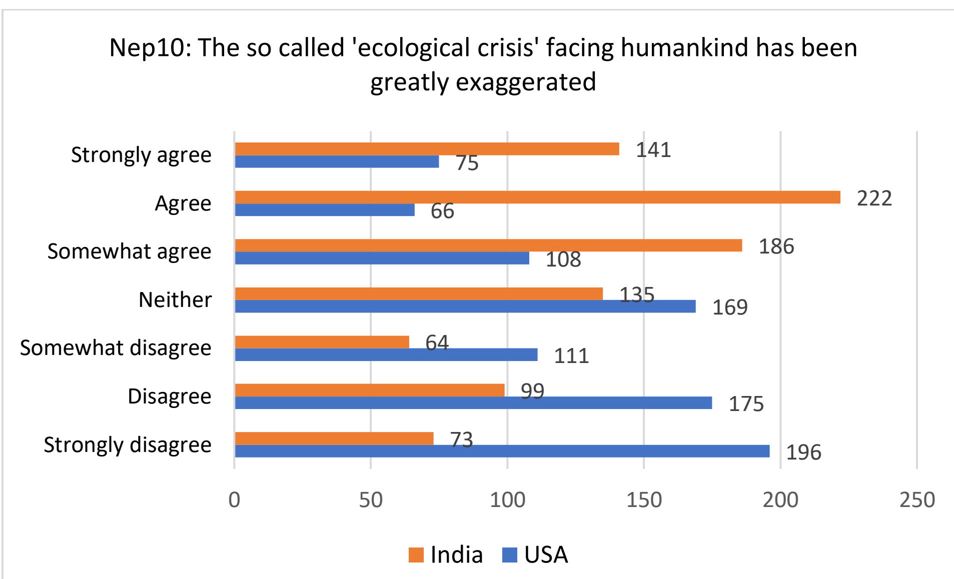

Figure 21 - Cross-national distribution of responses to Nep10

Most respondents from both countries largely agreed with the statements measuring the environmental concern dimension of the NEP scale. Among items measuring the second NEP dimension of anthropocentricism, the items on which both groups did not consistently agree or disagree had to do with the belief that the current ecological crisis is being greatly exaggerated, and the belief that humans will eventually learn enough about nature to be able to control it. More Indian respondents think that over time, people will be able to control nature than U.S respondents, who largely disagreed with this belief statement.

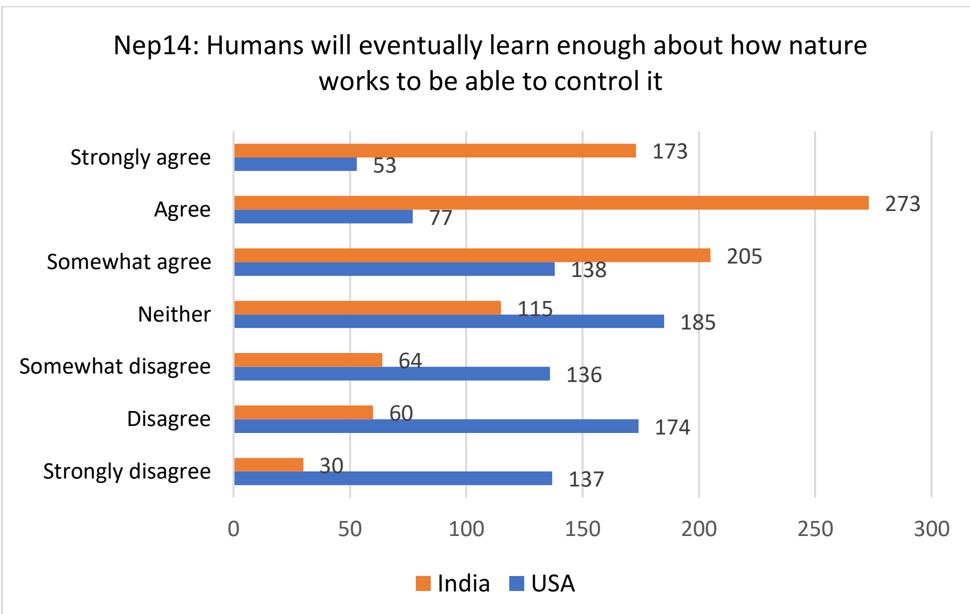

Figure 22 - Cross-national distribution of responses to Nep14

For nearly all the items measuring mutualistic wildlife value orientations, more participants from India either agreed or strongly agreed with statements than U.S. respondents did. While most participants across both groups seem to agree that wildlife crimes have consequences such as biodiversity loss, depletion of natural resources, and species extinction, a substantially higher number of participants from India strongly agreed with that statement than U.S. participants did. When it comes to the scale of ecological impacts that wildlife crimes have, participants from both groups agreed that these impacts spillover into surrounding communities and areas, but not as many participants agreed strongly with this statement even though among those who did, there were higher numbers of participants from India than the U.S. Moreover, a somewhat similar number of U.S. respondents 'strongly agreed', 'agreed', 'somewhat agreed', and 'neither agreed nor disagreed' with the statement that wildlife crimes such as the illegal trade in exotic species can cause the spread of deadly viruses and pathogens from animals to humans. This was not the case for Indian respondents who mostly either agreed or strongly agreed with that statement. When indicating whether they thought that conservation organizations help to actually combat the issue of wildlife crime and reduce its impacts, agreement did not seem as strong even though most participants across both groups did agree or somewhat agree with the statement. Those who strongly agreed that every citizen is responsible for mitigating the impacts of wildlife crime were mostly Indian participants. For U.S. participants, the most common responses were either 'somewhat agree' or 'neither agree nor disagree' on all three ascription items. While Indian participants rated 'every citizen' and 'the authorities' as somewhat equal in who they thought should take responsibility, U.S. respondents primarily agreed that the authorities should be responsible, followed by the public, and then the self.

While most U.S. and Indian participants largely agreed that they ought to donate money to conservation organizations to help reduce wildlife crime, most U.S. respondents indicated that they would not feel guilty if they did not donate money to conservation organizations whereas most Indian respondents largely agreed that they would feel guilty if they didn't donate money to conservation organizations for wildlife crime reduction.

Most U.S. respondents disagreed that they felt morally obligated to donate money to conservation organizations for wildlife crime reduction, but most Indian respondents largely agreed with this statement. Although most U.S. participants did not feel morally obligated to donate money for wildlife crime reduction, as seen in Figure 45, most of them, in fact, indicated that they felt donating money to conservation organizations for this cause was the 'right thing to do'. Another item whose responses diverge from U.S. participants' responses to PN3 – which assesses whether they would feel guilty by not donating money – is the final item in the scale measuring personal norms in which most participants from both countries agreed that they would feel good about themselves if they donated money to conservation organizations to help reduce wildlife crime. The number of respondents from India who strongly agreed with this statement was more than twice the number of U.S. respondents who expressed strong agreement with the statement.

Visual representations of cross-national responses to these individual items from both the planned behavior and value-belief-norm models are provided in Appendix J.

Demographic Factors

Most of the respondents across both groups who expressed stronger intentions to donate money to conservation organizations were between 18 and 34 years old. Those who identified as female slightly outnumbered those who identified as male in their willingness to donate money, however among those who said they would definitely be donating money within the next month, male participants slightly outnumbered female participants. Further, most respondents who indicated a high willingness to donate money reported earning between $20,000 and $40,000 per year in the U.S. and between INR 2,50,000 and INR 5,00,000 in India. Also, most of the respondents across both groups who expressed higher willingness to donate money reported having completed at least a bachelor's degree, with the next most frequent category being those who had completed at least a master's degree. Moreover, respondents who indicated they were employed full-time or self-employed were the ones who expressed most willingness to donate money. Finally, most of the participants who were more willing to donate money reported their political ideologies as being neither conservative nor liberal, with the next most frequent category being those who considered themselves to be ‘very liberal’.

CHAPTER FIVE: DISCUSSION

Research Questions and Objectives

This dissertation is set against the backdrop of a noticeable lack of three things that, due to their absence, prevent the development of a holistic understanding of a wicked problem such as wildlife crime. First, there is remarkably little communication-based research on wildlife crime. Second, there is a dearth of representation of non-Western communities, especially those in developing economies, in environmental communication and conservation social science research. Third, interdisciplinary research on wildlife crime is growing but still occurs primarily outside the domain of environmental communication and environmental psychology, which explains the lack of evidence of salient social-psychological factors that may drive or impede the adoption of conservation behaviors related to curbing wildlife crime, especially factors that may influence the success of conservation communication campaigns.

Against this backdrop, my broad objectives in conducting this research were to: 1) Determine the theoretical structure of behaviors linked to reducing wildlife crime – such as donating money to conservation organizations working to curb it; and 2) Determine whether the same factors predicted these behaviors in two different national samples.

To meet these objectives, I asked two overarching research questions:

- ***RQ 1:*** Which social-psychological factors best explain donation intentions to help reduce wildlife crime?
- ***RQ 2:*** How do the responses of participants from India compare to those of participants from the U.S.A.?

To answer both these questions, I tested two major theories of environmental behavior and conducted confirmatory factor analyses and structural equation modeling to determine how well existing scales measure the latent constructs in these theoretical models, and to determine the relationships between those latent constructs, thereby identifying factors from the two theories that most strongly predict donation intentions to help reduce wildlife crime. Secondly, I conducted this research in the form of a cross-national survey to demonstrate and compare how well each of the two theories performs in predicting these intentions.

Key Findings

The primary finding in this dissertation is that the theory of planned behavior performs better than the value-belief-norm theory at predicting intentions to donate money to conservation organizations to reduce wildlife crime. The theory of planned behavior explained greater variance in intentions to donate money to conservation organizations to help reduce wildlife crime in both U.S. (R^2 = 66.2%) and Indian (R^2 = 71.9%) samples, than either the original value-belief-norm theory model (USA R^2 = 60.8%; India R^2 = 56.2%), or the modified value-belief-norm model with wildlife value orientations did (USA R^2 = 61.1%; India R^2 = 56.5%).

Despite its better performance, the manner in which the TPB's exogenous variables predicted the outcome variable was surprising because, as the multivariate analysis revealed, attitudes toward the behavior did not significantly predict behavioral intention in either group. Further, had this study only presented correlations and linear regressions as findings, the relationship between attitudes and intentions would have been significant as they were both positively and strongly correlated in both samples. Therefore, this dissertation also underscores the importance of path analysis approaches such as structural equation modeling to demonstrate precisely how each predictor variable behaves in a multivariate model.

Most U.S. respondents largely disagreed that they planned to or would definitely donate money to conservation organizations within the next month whereas most Indian respondents largely agreed that they were willing to and would definitely donate money.

The value-belief-norm models – both the original one with New Ecological Paradigm measures and the modified one with mutualistic wildlife value orientations – were a lot more complicated to identify and fit. They were also affected by issues of low scale reliability and lack of convergent validity, particularly when it came to the Indian sample. The structural models for both Indian and U.S. groups for the value-belief-norm model were different; this was not based on whether hypothesized relationships were found, but rather on the non-significance of regression coefficients in the multivariate SEM analyses.

Across both the theories, there were four direct predictors of intention – attitude toward the behavior, subjective norms, perceived behavioral control, and personal norms. For Indian participants, perceived behavioral control mattered the most, followed by subjective norms, personal norms, and attitude – in that order. For U.S. participants, personal norms mattered the most when it came to predicting intentions to donate money to conservation organizations to help reduce wildlife crime, followed by perceived behavioral control, subjective norms, and then attitude – in that order. The most notable differences between group responses either because there were divergent responses or because one group expressed much stronger agreement than the other, were related to subjective norms, egoistic values, ascription of responsibility, personal norms, and intention to donate money.

Theoretical Implications

In this section, I discuss issues related to conceptualization, operationalization, measurement, scale development, etc. relevant to both the theories tested in this dissertation. Implications of the findings discussed here are aimed primarily at other scholars who may be able to address some of these concerns in their future work or may be able to solve some of the problems I ran into. Practical implications for conservation and communication practitioners are discussed in a later section.

Theory of Planned Behavior

For the most part, given the simplicity of the TPB model, the analysis and results were straightforward. Given that all latent factors in the TPB model met the criteria for convergent and discriminant validity, and had high scale reliability, the absence of a significant relationship between attitude toward the behavior and intention to donate was surprising but looking at the significant positive correlations between the three exogenous variables in this model (attitude, subjective norms, and perceived behavioral control), it is plausible that the influence of attitude on intention could have been dissipated through its covariance with the two other exogenous latent factors, leaving no significant direct association with intention.

Other researchers have tried to explain the gap between attitudes and behavior by suggesting that if the social normative, familiar, or cultural environmental of an individual espouses views that are antithetical to the behavior being measured, attitudes are unlikely to influence behavior strongly, or that assessing attitudes and behaviors in different time periods can cause this gap, and attitudinal measures that are either too broad or too narrow based on the behavior being measured are also likely to impede the attitude—behavior relationship (Kollmuss & Agyeman, 2002). However, these issues would be unlikely to afflict the relationship between these two factors in this dissertation because behavior-specific attitudinal measures were used which showed high scale reliability as well as convergent validity. While the majority of research using the theory of planned behavior tends to demonstrate a significant relationship between attitudes and intentions, the impact of attitudes on behaviors has been known to be small as well (Kollmuss & Agyeman, 2002). In their low-cost/high-cost model explaining the gap between attitudes and environmental behaviors, Diekmann & Preisendörfer (1992) suggest that people are likely to engage in environmental behaviors that have the least cost – whether financial, psychological, or in the form of time and effort needed to perform the behavior. Given that, in this study, the outcome behavior being assessed would have required respondents to bear financial, cognitive, and resource-related costs, it is plausible – based also on the large number of U.S. respondents who did not intent to donate money – that these associated costs of performing the behavior were unacceptable or out of line with respondents' priorities. Additionally, this is not the only study in which attitudes did not relate significantly to intentions/behaviors (Valle et al., 2005). In their cross-national comparison of the theory of reasoned action, the norm activation model, and the VBN, Cordano et al. (2011) found that attitudes did not significantly predict intentions (p. 645) for Chilean respondents, and this relationship was just barely significant for U.S. respondents. In explaining this finding, Cordano et al. cite Ajzen (1985, 1991), who suggested that whether or not a particular TPB predictor is likely to play a significant role varies with the kind of behavior being studied. Therefore, although it is not possible to say from cross-sectional survey data what may have caused this unexpected finding, the fact that the attitude—intention relationship was non-significant in both the U.S. and the Indian context merits further investigation, particularly in the context of other wildlife-related conservation behaviors.

The measurement and structural equation models for both countries were the same for the TPB when it came to the indicators and associations between latent factors, however regression coefficients and factor loadings were different across both groups. This suggests that while it is likely that the items being used to measure the latent factors are doing a good enough job of measuring those latent variables in both countries, some of the items may be contributing more or less to the latent factor, and that the strength of association between the indictor items and their latent factors, and between the latent factors themselves may be different in different samples of respondents. That said, the TPB holds up well even outside the predominantly Western and developed nations context in which it is largely applied. The findings from the SEM for the TPB help to cross-validate and, in fact, demonstrate, that not only is this theory able to predict this unique type of conservation behavior (related to wildlife crime reduction), but it is also able to retain its measurement and theoretical structure cross-nationally.

In answering RQ1 then, I found that from the theory of planned behavior, perceived behavioral control and subjective norms were the salient factors that predicted intentions to donate money to conservation organizations to help reduce wildlife crime, and while attitude did not play a salient role, their significant positive covariance with these two factors suggests that may matter but not directly, as initially expected.

In addressing RQ2, I was not surprised that subjective norms measures seemed to have stronger agreement from Indian respondents than from U.S. respondents given that social norms play a significant role in the collective type of society that exists in India (R. W. Liu et al., 2022; Shalender & Sharma, 2021; Taufique & Vaithianathan, 2018). Moreover, the stronger agreement with self- and response-efficacy items suggests that more Indian participants were confident in their ability to donate money to conservation organizations, and had more availability of sufficient resources, time, and opportunities than U.S. participants. This self-confidence and availability of resources, time, and opportunities seemed to play an important role in Indian participants' strong intentions to donate money, along with the belief that making these donations would actually help conservation organizations reduce wildlife crime. On the other hand, most U.S. respondents said they did not have sufficient resources to donate money and showed low response efficacy compared to Indian respondents. Practical implications of these cross-national findings and differences are discussed in a later section.

Overall, the primary finding that the TPB performs much better than the VBN at predicting intentions to engage in a wildlife crime-related conservation behavior cross-nationally, raises important questions about the type of behavior this might be. One may suggest that the act of donating money, being charitable, lets us describe donating money to conservation organizations to help reduce wildlife crime as a pro-social or values-beliefs-or-norm-driven behavior, and while a part of that argument may well be valid given the role of personal norms in this dissertation, it is important to note that the strongest predictors were TPB constructs. Considering that the theory of planned behavior is rooted in the premise of self-interest or rational-thought-based-behaviors, the findings from this dissertation would suggest that donating money to conservation organizations to help reduce wildlife crime is a rational and planned behavior, adopted more out of self-interest than out of a pro-social motive that underlies the value-belief-norm model. More specifically, the difference between how much variance each of these two theories explain in the donation intentions outcome is larger for India (15%) and smaller for the United States (5%) which may indicate that this behavior could be characterized as more of a planned, rational act for Indian respondents but that it may be more of a mixed bag for U.S. respondents as personal norms play a larger role in the U.S.

Original Value-Belief-Norm Model

A handful of interesting findings regarding the value-belief-norm model emerged in this dissertation, especially when it comes to cross-national comparisons. First, although the SEM for this model did produce an acceptable fit for the Indian sample, the consistent lack of scale reliability and convergent validity makes it difficult to generalize the findings from the Indian sample. While the theory held up for U.S. respondents, showing clear relationships between values, beliefs, personal norms, and intention, I would say the theory – in its simplest form – did not hold up Indian respondents as well. For instance, biospheric values – which did demonstrate convergent validity for both samples – had no significant influence on ecological worldviews dimensions for Indian respondents, but this relationship was significant for U.S. respondents. Similarly, although altruistic values were the strongest predictors of ecological worldviews in the Indian sample, their measures did not meet the requirements for establishing convergent validity. With respect to egoistic values, two of the five items had to be removed from the analysis for both groups, and a third had to be removed for the Indian sample, leaving a two-item latent factor which is not ideal in CFAs. Interestingly, however, egoistic values were among those variables on which cross-national responses differed substantially. For instance, having control over others' action, having authority over others, and being influential were overwhelmingly rated as "extremely important" by Indian participants who far outweighed U.S. respondents who agreed, whereas most U.S. participants largely disagreed with those values statements.

Tables 10 and 11 show that scale reliability is consistently above the 0.7 threshold for Cronbach's alpha in the U.S. sample whereas several scales have low internal consistency in the Indian group. The inconsistency and lack of reliability of measures raises important questions about where and how these measures were developed, and further underscores the need for cross-validating scales that are so widely used in environmental communication and environmental psychology research. This brings up another two-fold concern – most studies that apply or test this theory, like many other social-psychological theories of environmental behavior and communication, are conducted in Western, industrialized, rich countries; and these are also the countries where scholars develop and validate their scales. In most cases when these theories are applied in non-Western countries or emerging economies, scholars do not resort to confirmatory factor analyses or path analyses etc. that could validate both the measurement and structural models that have been accepted in the Western countries where these scales and theories were developed and tested (R. W. Liu et al., 2022).

Within the original VBN model, while there were items measuring altruistic and egoistic values that did have poor factor loadings and were eventually removed from one or both of the countries' SEM analyses, the most challenging hurdle to navigate was presented by the New Ecological Paradigm scale which, despite being criticized for its reliability and validity as a measure of general environmental beliefs, has continued to be applied in studies using the VBN theory as a unidimensional construct or in various permutations and combinations of the complete 15-item NEP scale (Carfora et al., 2021; Dunlap, 2008; Dunlap et al., 2000; Gkargkavouzi et al., 2019; Han, 2015; Ntanos et al., 2019; van Riper & Kyle, 2014b).

Following one of the rare instances in which scholars assessed the dimensionality of the NEP scale using confirmatory factor analysis, a primary takeaway from the results of this dissertation research has to do with the inherent multi-dimensionality of the NEP scale (Amburgey & Thoman, 2012). Ecological worldviews, as operationalized by the NEP scale, emerged as having three dimensions – environmental concern or ecocentrism, anthropocentricism, and limits to growth (Ntanos et al., 2019). Despite demonstrating this multi-dimensionality, scholars did not appear to modify the hypothesis associated with ecological worldviews in the VBN model. For instance, if the NEP is multi-dimensional with each dimension reflecting a different view of human-nature relationships (e.g., human domination vs. anti-exemptionalism), why would each of those dimensions continue to relate positively to awareness of consequences in the VBN chain of effects, or why would biospheric and egoistic values have the same valence of effect on the different NEP dimensions? In my review of the literature, I found that these questions are not accounted for in the way we use these scales. For example, anthropocentricism among Indian respondents is negatively associated with a positive attitude toward the behavior, which would logically be expected. However, this relationship was positive for US respondents, even if minutely so. Additionally, if anthropocentricism is a dimension of NEP, then would we not expect biospheric values to be negatively related to anthropocentricism, as was the case in the Indian sample in this dissertation? Moreover, building a 15-item scale into a questionnaire only to discard a third of those items from subsequent factor analyses is an inefficient approach to measuring and including ecological worldviews in this theoretical model. Essentially, based on what I found, the challenges I faced, what I have read and learned about cross-validating measurement and structural models, I believe it is entirely possible to develop a more helpful measure of ecological worldviews – even if it is the multi-dimensional NEP scale – to better predict and explain environmental behaviors without continuing with business-as-usual wherein it is assumed that all values (biospheric, altruistic, egoistic) will be positively or negatively associated with a singular unidimensional concept of NEP.

Comparing the Original and Modified VBN Models

According to the SEM for the original VBN model, altruistic and egoistic values predicting the two NEP dimensions I found and included in the model, but biospheric values had no significant relationship with either NEP dimension. Moreover, having dropped one indicator of altruistic values and three indicators of egoistic values from the Indian sample, and having eliminated two egoistic values indicators from the U.S. sample, I expected to end up with two different measurement models for the two groups.

When comparing the original NEP-based value-belief-norm model to the modified version in which mutualistic wildlife value orientations replaced NEP as a measure of ecological worldviews, I found that while the variance explained by the WVO-based model was not that different from the NEP-based model, the structural models were, in fact, different. For instance, biospheric values played a significant role in predicting mutualistic wildlife value orientations which, themselves, significantly and positively predicted awareness of consequences, and so on, until personal norms positively and significantly predicted intention to donate money to conservation organizations.

The finding that the WVO-based VBN model was not only a well-fitting model but that it had slightly better model fit goes to show that there is, indeed, potential to replace the New Ecological Paradigm scale as a measure of ecological worldviews and, instead, use a behavior-specific measure of value orientations, and while there has been cross-validation of the wildlife value orientations measures, these findings underscore the importance of cross-validating these measures and models in non-Western countries and emerging economies as well (De Groot & Steg, 2007; Liordos et al., 2021; Teel et al., 2007).

Despite the roadblocks with reliability, validity, and cross-validation of measures in the VBN models – both NEP-based and WVO-based – the theory does predict a type of conservation behavior linked to reducing wildlife crime, and it does so in two different countries. There is certainly scope for improving the VBN's ability to predict and explain these behaviors cross-nationally in the future by being more selective about measures, and by consistently confirming and revising measurement and structural models with findings from non-Western countries and emerging economies where this theory is tested (Sharma & Gupta, 2020).

Practical Implications for Conservation Communication

Based on the results that answered both the research questions, in this section, I will translate some of the findings and theoretical implications into practical recommendations for conservation communication designers or professionals and practitioners in conservation tasked with public communication and campaign message design.

As I point out above, donating money to conservation organizations for reducing wildlife crime may sound like and even be framed as a charitable, pro-social behavior in conservation campaigns and social marketing materials, but the predominance of the TPB's constructs in predicting intentions to donate money for this cause should prompt conservation practitioners in strategic communication to pause and consider whether their messages to diverse, cross-national audiences are appealing to or evoking the right factors. For example, such campaigns in the U.S. may tend to focus more heavily on personal norms and that may be warranted, as the results show, but outside the U.S. and even within it, organizations risk alienating audience members who are not drive by personal norms but would be willing to donate money for other reasons such as having the time, money, confidence, and opportunities to donate, or believing that doing so is likely to really help conservation organizations combat wildlife crime.

Conservation professionals tasked with designing campaign communications for Indian audiences would do well to include normative messaging that highlights social normative engagement with the behavior they are calling for in campaigns. For example, including a message in a campaign against wildlife crime that tells audience members that those who they look up to or those who matter most to them would want and expect them to perform the target behavior may enhance the effectiveness of that message and influence the success of the campaign. This social normative aspect of such a message may matter more to audiences in India than in the U.S. but it would still be important for U.S. audiences regardless.

Conservation campaign messages seeking behavioral engagement in India and the United States should also build efficacy among potential donors such as by suggesting that requested donations are of a value that is acceptable to those audience segments, or by having an adjustable sliding scale so that donors can choose the amount they feel most comfortable donating. Relatedly, given the low response efficacy among U.S. participants in this dissertation, I would recommend that conservation organizations be specific about targeting audience segments that are not resource-deficient, and that these organizations should explicitly communicate how they would use the donations they receive to take tangible action or make changes or improvements that will actually help reduce wildlife crime eventually. Showing donors that their time, resource, and action actually builds towards something can be crucial for the success of a campaign to prevent wildlife crime. Further, by making the process of donating money as efficient and easy as possible to use minimal time, conservation organization can further enhance self-efficacy among potential donors.

Additionally, it is important to consider that this study was conducted during the COVID-19 pandemic. In the early days of this pandemic, news stories were published that attributed the origins of the pandemic to illegal wildlife trade, specifically, the trafficking of wild animals such as pangolins or bats to wet markets in Wuhan, China, where the virus responsible for the COVID-19 disease was traced back to by the WHO. The international coverage and unprecedented attention that illegal wildlife trade was getting in this context, allowed some members of the public to connect the dots between wildlife trade and the spread of deadly pathogens and zoonotic diseases. It is not possible to gauge the extent to which participants from both countries were aware of or had been exposed to news coverage linking the COVID-19 pandemic to international wildlife trade, however, based on their responses to the item featured in Figure 40, a relatively similar number of U.S.

respondents ‘strongly agreed’, ‘agreed’, ‘somewhat agreed’, and ‘neither agreed nor disagreed’ with the statement that wildlife crimes such as the illegal trade in exotic species can cause the spread of deadly viruses and pathogens from animals to humans. This was not the case for Indian respondents who mostly either agreed or strongly agreed with that statement. I mention this not because I am able to report a measured impact of information about the COVID-19 pandemic on participants’ responses in these surveys, but more so because the extent to which audiences are aware of the range of impacts an issue has and what problems it causes is likely to contribute to the success or failure of a conservation campaign message about that issue. For instance, although most participants from both groups largely agreed that wildlife crimes cause biodiversity loss, species extinction, depletion of natural resources, and have far-reaching environmental consequences on surrounding areas and communities, fewer Indian and U.S. American respondents agreed that conservation organizations help curb wildlife crime and mitigate its impacts. If audiences do not believe that conservation organizations are effectively addressing the issue and impacts of wildlife crime, I would argue that is likely to impede the efficacy of any campaign communication from these organizations seeking donations from such audience members. To pre-emptively avoid a loss of donor engagement, conservation organizations should, whenever possible, include evidence of the impact their work has had on combatting wildlife crime, or provide evidence of how donations from contributing individuals have been used to mitigate some of the impacts of wildlife crime. This is not to say that such impact evaluations may not already exist, but they are hardly made public. If conservation organizations do not transparently disclose the impact of their work to reduce wildlife crime, for instance, audiences may not consider the issue or that organization's work to manage it as important. Organizations must, therefore, ask themselves – Would their prospective supporters donate money to an organization whose work, impact, effectiveness, or success they are not aware of?

Despite the myriad issues associated with the NEP scale, looking at item-level responses provided some valuable insight that could have practical relevance. One of the NEP items states that the ongoing ecological crisis has been greatly exaggerated (see Table 10 for specifics). Respondents from India overwhelmingly agreed with that statement while respondents from the U.S. largely disagreed with it. This was surprising because most participants from both countries had largely agreed on most of the biospheric values and mutualistic wildlife value orientations measures. Considering this particular NEP item is similar in the sense that it is seeking to reflect an eco-centric belief for those who disagree with the item, I would have expected to see disagreement from both groups. However, based on those findings, it then becomes important to acknowledge that if audiences believe that the current ecological crisis has been exaggerated, conservation organizations communicating about wildlife crime and trying to gain support through donations may need to focus their messaging on other salient factors that predict intention to donate within this community – such as by centering their messages on building self- and response efficacy, by invoking social norms, appealing to biospheric and altruistic values, and by evoking mutualistic wildlife value orientations.

It is important to also note that guilt-shaming people into donating to such causes may not work for all audiences. For instance, it was mostly Indian respondents who agreed that they would feel guilty if they did not donate money to conservation organizations to help reduce wildlife crime, and that they feel morally obligated to donate money for this cause.

U.S. respondents largely disagreed that they would feel guilty if they did not donate money, and also disagreed that they feel morally obligated to do so. This was despite overall agreement from both groups that they felt they ought to donate money for this purpose, and that doing so would be the right thing to do, and it would make them feel good about themselves. In most cases, strong agreement largely came from Indian respondents whereas U.S. respondents tended to opt for a neutral response more often. When appealing to personal norms in their campaigns or messaging, therefore, conservation organizations might benefit from highlighting the 'feel good' aspect of charitable donation behaviors, but should not universally aim to make people feel guilty or obligated to donate money unless they have a well-rounded understanding of their target audience's beliefs.

It might also be helpful for conservation organizations interested in running campaigns on wildlife crime prevention to get an idea of the socio-demographic details of their target audiences. In this dissertation, for example, those who expressed strong intentions to donate money to conservation organizations were mostly between the ages of 18 and 34; earned between U.S. $20,000 - $40,000 or INR 2,50,000 – INR 5,00,000 per year; had completed at least a bachelor's degree, were either employed full-time or self-employed, and indicated a political ideology that was neither conservative nor liberal.

It is also worth noting that although most Indian respondents made between INR 2,50,000 and INR 5,00,000 per year – which, based on current exchange rates, is the equivalent of U.S. $3,140 and $6,282 per year – the number of Indian respondents who strongly agreed with having sufficient resources to be able to donate money to conservation organizations for wildlife crime reduction was nearly three times the number of U.S. respondents who strongly agreed with the same statement (see Figure 23). For context, most U.S. participants earned less than $20,000 per year. However, since I did not collect information on participants' place of work or residence, it is not possible to estimate the average cost of living for either group. This is not to say that those who reported earning higher incomes did not intend to donate money, but rather to say that those who seemed most willing to donate money did not appear to have the most disposable income which suggests that income may not always be a barrier to engaging in donation behavior.

Key Contributions

The major contributions of this dissertation are two-fold: 1) The application and rigorous testing of two major theories of environmental behavior in an entirely different context of wildlife crime-related conservation behaviors, thereby identifying the factors and theoretical models that are salient to predicting intentions to donate money to conservation organizations to reduce wildlife crime, and 2) The cross-national test of these theories in the context of wildlife crime prevention, which leads to the identification and confirmation of reliable measurement models, and the identification of the theoretical structure of these behaviors as predicted by the two theories in two different countries, thereby building new empirical knowledge, advancing theory, and underscoring the value of having more diverse and inclusive environmental social science research.

Not only does the cross-national comparison advance empirical and theoretical research in environmental communication (Takahashi, Duan, et al., 2021; Takahashi, Metag, et al., 2021), but it provides the first-known empirical data on social-psychological determinants of conservation behaviors related to wildlife crime from India and, to my knowledge, the United States as well. This dissertation demonstrates how well each of the two theories – the theory of planned behavior (Ajzen, 1991), and the value-belief-norm theory (Stern et al., 1999) – performed across two national samples to predict the same outcome.

Moreover, this dissertation also demonstrates that mutualistic wildlife value orientations (WVOs) can replace the New Ecological Paradigm scale (NEP) as a measure of ecological worldviews without affecting the model fit, specifically in the context of wildlife-related behaviors as predicted or explained by the value-belief-norm (VBN) model (Manfredo, Teel, Don Carlos, et al., 2020).

With both theoretical and empirical contributions, this dissertation expands the purview of environmental communication and environmental psychology research to include wildlife crime-related behaviors and aspects and underscores the need for scholars to move beyond predominantly Western, industrialized, established economies and be more inclusive in the communities and regions they study.

This research also emphasizes the importance of developing and maintaining long-term cross-functional partnerships between academic researchers and conservation practitioners so that such mutually beneficial relationships can lead to effective management strategies to combat wildlife crime – a wicked problem that requires such integrated approaches to problem-solving. Sharing my findings with conservation organizations and practitioners as an accessible toolkit will be my way of taking a step towards building such a collaboration. In the future, I hope that a two-way relationship can develop through which social scientists can help practitioners better understand their audiences and better strategize their communication, while practitioners can provide valuable real-world data to help advance theory, science, and conservation goals.

Future Research

While identifying salient drivers of intentions to donate money to reduce wildlife crime is certainly a necessary first step towards building a theory of wildlife conservation behaviors aimed at combatting wildlife crime, it is also important to keep in mind that this dissertation only measures predictors of behavioral *intention* and not behavior itself. As prior research has shown, just as there may be a set of factors that facilitate the adoption of such behaviors, there are also barriers to these behaviors (Kollmuss & Agyeman, 2002). As future research builds on and further develops our understanding of the factors that drive wildlife crime-related conservation behaviors, it would also be helpful, not just for theorizing, but also for making practical recommendations to conservation professionals, to know which factors may act as barriers to engaging in such conservation behaviors, and which communities or populations are especially likely to encounter those barriers.

Additionally, future research could expand on this dissertation by applying and testing these theories and models in other countries as well, especially in parts of the world that tend to get overlooked in environmental communication and environmental psychology research. Not only is this likely to produce interesting empirical data from understudied regions, but it will go a long way in improving the reliability and validity of some of the most widely used measures and scales in environmental social science research.

On the other hand, it could lead to the development of new scales that are more specific to wildlife-related behaviors. For example, this dissertation uses measures and scales adapted from other research – albeit research on environmental behaviors – but not from work that has focused specifically on and used validated measures to assess wildlife crime-related conservation behaviors. Therefore, future research will likely have to dig its heels into scale development and cross-validation.

Using the cross-sectional survey as a steppingstone, future research could design and conduct experiments to test causal chain of effects and determine whether the measurement and structural models found to fit the data in this dissertation would also be reproduced in an experiment. An experiment would be able to assess not only the paths through which direct and indirect causal effects occur but would also be able to test an actual conservation communication campaign message on wildlife crime prevention for its cognitive, affective, and behavioral effects, and could share the results with conservation practitioners or organizations to help them optimize their strategic communication and message design. A path analysis from experimental data could demonstrate direct, indirect, mediation, and moderation effects which could provide much deeper insight to both scholars and conservation professionals tasked with public communication and strategizing.

Those interested in the theoretical or methodological implications of the findings in this dissertation could, for instance, investigate whether the ability of attitude to predict intention was being dissipated through its covariances with subjective norms and perceived behavioral control or whether attitudes, even though they're known to sometimes have small effects, are necessary to include in the model. That said, it would be interesting to develop an integrated model along the lines of what others have tested before to demonstrate whether factors that are strong and known predictors of wildlife crime-related conservation behaviors can be integrated into a single model that retains parsimony but has great predictive potential (Bamberg & Möser, 2007; Carfora et al., 2021;

Gkargkavouzi et al., 2019; Klöckner, 2013; Montaño & Kasprzyk, 2008). Personally, I would like to expand on this research by examining other kinds of wildlife-related conservation behaviors, or specifically, other behaviors linked to reducing wildlife crime such as information-seeking behaviors, or signing petitions, publicly showcasing support for the cause etc. Such assessments would add to the recommendations and findings from this dissertation and would make for a more comprehensive guide for conservation organizations who wish to understand their audiences better and who seek to optimize their communication strategies and messages for different audiences.

Finally, and this may be far-fetched or idealistic, but my hope is that as conservation social science is embracing its interdisciplinarity and as social scientists and practitioners are now working together more frequently than they did before, there may be room for academic researchers and conservation organizations to collaborate on such projects. This dissertation already demonstrates to conservation organizations working in India and the U.S.A. how a sample of their audiences currently think and feel about wildlife crime and its reduction. I believe the findings from this dissertation will aid these organizations in identifying factors they can leverage in their approach to designing wildlife crime prevention communication materials and campaigns in these communities.

Limitations

One of the limitations of this dissertation is inherent to the method – surveys rely on self-reported data which can be prone to social desirability and other kinds of biases that prompt respondents to select options that they think the researcher would want them to select or to avoid seeming 'undesirable'. Questions about pro-environmental values, beliefs, attitudes, etc. may evoke such biases though so I paid special attention to my question wording in designing the survey. Furthermore, the use of Qualtrics panels have recently sparked concerns about their vulnerability to automated bots that produce unreliable data. However, to avoid this problem, I used two attention checks and a speeding check to ensure that I only got complete responses. Even so, within the complete responses returned by Qualtrics, I noticed frequent straight-lining behaviors, especially among U.S. respondents, and a large number of U.S. respondents selecting the 'neither agree nor disagree' option while answering questions.

Relatedly, if I was to do this all over again, I would consider using item-specific response options rather than the standard Likert-type 7-point or 5-point agree-disagree scales (Saris et al., 2010). Using item-specific response options may improve not only reliability and validity, but also the quality of data interpretations.

Additionally, surveys can be subject to measurement error, but they have higher external validity and generalizability. Considering that no previously validated scales specifically to measure wildlife crime-related behaviors existed, this dissertation draws from prior research on environmental behavior, natural resource management, environmental tourism, and other studies that have examined determinants of willingness to pay or willingness to donate, and studies that have compared the theory of planned behavior to the value-belief-norm theory. While the pilot test and pre-test interviews helped identify potential issues and make revisions to the survey instrument, the low reliability and convergent validity for VBN measures for the Indian sample could be an indication of measurement error.

This survey was only accessible to participants from both countries who were fluent in English. In the future, I hope to work with collaborators to develop regional language translations of such questionnaires as well, for a more in-depth look at these relationships. By nature of the method and data, findings from this dissertation are restricted to making correlational statements about relationships between constructs which, although not as powerful as establishing causality, is an important first step towards building theory to explain and predict wildlife crime-related conservation behaviors.

Finally, it is important to keep in mind that this dissertation only measures predictors of behavioral intentions, and not behavior itself. Therefore, I cannot extrapolate from these findings and endeavor to explain behaviors without knowing what might impede the transition from intention to behavior in the context of wildlife crime reduction.

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APPENDIX A: MULTIVARIATE NORMALITY TESTS IN R

$multivariateNormality (USA)

	Test	Statistic	p value	Result
1	Mardia Skewness	154637.914481546	0	NO
2	Mardia Kurtosis	186.295829703372	0	NO
3	MVN	<NA>	<NA>	NO

$multivariateNormality

	Test	Statistic	p value	Result
1	Mardia Skewness	163327.797601619	0	NO
2	Mardia Kurtosis	188.924204987438	0	NO
3	MVN	<NA>	<NA>	NO

APPENDIX B: THEORY OF PLANNED BEHAVIOR CFA MODEL FIT STATISTICS

Raw output from RStudio

```
## lavaan 0.6-11 ended normally after 112 iterations
##
##   Estimator                                ML
##   Optimization method                  NLMINB
##   Number of model parameters              108
##
##   Number of observations per group:
##     USA                                   900
##     India                                 920
##   Number of missing patterns per group:
##     USA                                     1
##     India                                   2
##
## Model Test User Model:
##                                Standard      Robust
##   Test Statistic               1349.825     878.601
##   Degrees of freedom                196         196
##   P-value (Chi-square)            0.000       0.000
##   Scaling correction factor                   1.536
##        Yuan-Bentler correction (Mplus variant)
##   Test statistic for each group:
##     USA                         912.975     594.256
##     India                       436.850     284.346
##
## Model Test Baseline Model:
##
##   Test statistic              22974.689   13301.927
##   Degrees of freedom                240         240
##   P-value                         0.000       0.000
##   Scaling correction factor                   1.727
##
## User Model versus Baseline Model:
##
##   Comparative Fit Index (CFI)     0.949       0.948
##   Tucker-Lewis Index (TLI)        0.938       0.936
##
##   Robust Comparative Fit Index (CFI)          0.954
##   Robust Tucker-Lewis Index (TLI)             0.943
##
## Loglikelihood and Information Criteria:
##
##   Loglikelihood user model (H0)  -40966.728  -40966.728
```

```
##   Scaling correction factor                          1.698
##      for the MLR correction
##   Loglikelihood unrestricted model (H1)           NA         NA
##   Scaling correction factor                          1.594
##      for the MLR correction
##
##   Akaike (AIC)                       82149.457   82149.457
##   Bayesian (BIC)                      82744.169   82744.169
##   Sample-size adjusted Bayesian (BIC)       82401.057   82401.057
##
## Root Mean Square Error of Approximation:
##
##   RMSEA                               0.080       0.062
##   90 Percent confidence interval - lower        0.076       0.059
##   90 Percent confidence interval - upper        0.085       0.065
##   P-value RMSEA <= 0.05                        0.000       0.000
##
##   Robust RMSEA                                     0.077
##   90 Percent confidence interval - lower                 0.072
##   90 Percent confidence interval - upper                 0.082
##
## Standardized Root Mean Square Residual:
##
##   SRMR                               0.062       0.062
##
## Parameter Estimates:
##
##   Standard errors                          Sandwich
##   Information bread                          Observed
##   Observed information based on              Hessian
##
##
## Group 1 [USA]:
##
## Latent Variables:
##                Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##   Attitude_cfa =~
##    Att1           1.000                           1.223    0.888
##    Att2           1.037    0.031   33.068    0.000    1.269    0.894
##    Att3           1.069    0.034   31.879    0.000    1.308    0.907
##    Att4           1.079    0.030   35.754    0.000    1.320    0.926
##    Att5           1.071    0.036   29.360    0.000    1.310    0.900
##   SubNorms_cfa =~
##    SN1            1.000                           1.417    0.887
##    SN2            1.003    0.029   34.506    0.000    1.422    0.830
##    SN3            0.889    0.029   31.023    0.000    1.259    0.835
```

```
##   PBC_cfa =~
##    PBC1           1.000                          1.143    0.679
##    PBC2           1.251    0.073   17.079    0.000    1.429    0.749
##    PBC3           1.129    0.055   20.526    0.000    1.290    0.752
##    PBC4           1.144    0.064   17.919    0.000    1.308    0.731
##    PBC6           0.799    0.053   14.959    0.000    0.913    0.611
##   Intention_cfa =~
##    Int1           1.000                          1.558    0.845
##    Int2           1.083    0.027   40.481    0.000    1.688    0.944
##    Int3           1.088    0.028   38.573    0.000    1.695    0.949
##
## Covariances:
##                Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##   Attitude_cfa ~~
##    SubNorms_cfa     1.164    0.090   12.974    0.000    0.671    0.671
##    PBC_cfa          0.732    0.090    8.107    0.000    0.524    0.524
##   SubNorms_cfa ~~
##    PBC_cfa          1.058    0.093   11.387    0.000    0.653    0.653
##   Attitude_cfa ~~
##    Intention_cfa    1.027    0.089   11.591    0.000    0.539    0.539
##   SubNorms_cfa ~~
##    Intention_cfa    1.575    0.102   15.475    0.000    0.713    0.713
##   PBC_cfa ~~
##    Intention_cfa    1.356    0.101   13.420    0.000    0.762    0.762
##
## Intercepts:
##                Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##   .Att1           5.441    0.046  118.495    0.000    5.441    3.950
##   .Att2           5.280    0.047  111.651    0.000    5.280    3.722
##   .Att3           5.150    0.048  107.162    0.000    5.150    3.572
##   .Att4           5.257    0.048  110.662    0.000    5.257    3.689
##   .Att5           5.236    0.049  107.816    0.000    5.236    3.594
##   .SN1            4.133    0.053   77.669    0.000    4.133    2.589
##   .SN2            3.774    0.057   66.149    0.000    3.774    2.205
##   .SN3            4.468    0.050   88.851    0.000    4.468    2.962
##   .PBC1           4.747    0.056   84.594    0.000    4.747    2.820
##   .PBC2           3.291    0.064   51.721    0.000    3.291    1.724
##   .PBC3           4.239    0.057   74.114    0.000    4.239    2.470
##   .PBC4           4.057    0.060   68.055    0.000    4.057    2.268
##   .PBC6           4.777    0.050   95.934    0.000    4.777    3.198
##   .Int1           3.944    0.061   64.141    0.000    3.944    2.138
##   .Int2           3.489    0.060   58.562    0.000    3.489    1.952
##   .Int3           3.350    0.060   56.272    0.000    3.350    1.876
##    Attitude_cfa     0.000                          0.000    0.000
##    SubNorms_cfa     0.000                          0.000    0.000
##    PBC_cfa          0.000                          0.000    0.000
```

```
##    Intention_cfa    0.000                          0.000    0.000
##
## Variances:
##                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##    .Att1           0.401    0.052    7.685    0.000    0.401    0.211
##    .Att2           0.403    0.052    7.716    0.000    0.403    0.200
##    .Att3           0.368    0.040    9.237    0.000    0.368    0.177
##    .Att4           0.288    0.031    9.405    0.000    0.288    0.142
##    .Att5           0.405    0.050    8.030    0.000    0.405    0.191
##    .SN1            0.542    0.063    8.592    0.000    0.542    0.213
##    .SN2            0.910    0.083   10.977    0.000    0.910    0.310
##    .SN3            0.689    0.066   10.423    0.000    0.689    0.303
##    .PBC1           1.528    0.096   15.849    0.000    1.528    0.539
##    .PBC2           1.602    0.119   13.427    0.000    1.602    0.440
##    .PBC3           1.281    0.096   13.284    0.000    1.281    0.435
##    .PBC4           1.488    0.116   12.795    0.000    1.488    0.465
##    .PBC6           1.398    0.110   12.713    0.000    1.398    0.626
##    .Int1           0.976    0.094   10.330    0.000    0.976    0.287
##    .Int2           0.346    0.042    8.276    0.000    0.346    0.108
##    .Int3           0.318    0.045    7.043    0.000    0.318    0.100
##     Attitude_cfa   1.497    0.123   12.146    0.000    1.000    1.000
##     SubNorms_cfa   2.007    0.116   17.329    0.000    1.000    1.000
##     PBC_cfa        1.306    0.123   10.629    0.000    1.000    1.000
##     Intention_cfa  2.427    0.135   17.943    0.000    1.000    1.000
##
## R-Square:
##                   Estimate
##     Att1           0.789
##     Att2           0.800
##     Att3           0.823
##     Att4           0.858
##     Att5           0.809
##     SN1            0.787
##     SN2            0.690
##     SN3            0.697
##     PBC1           0.461
##     PBC2           0.560
##     PBC3           0.565
##     PBC4           0.535
##     PBC6           0.374
##     Int1           0.713
##     Int2           0.892
##     Int3           0.900
##
##
## Group 2 [India]:
```

```
##
## Latent Variables:
##                  Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##   Attitude_cfa =~
##     Att1              1.000                               0.875    0.814
##     Att2              1.000    0.044   22.855    0.000    0.875    0.801
##     Att3              1.167    0.051   23.088    0.000    1.021    0.815
##     Att4              1.064    0.049   21.713    0.000    0.931    0.844
##     Att5              1.017    0.054   18.846    0.000    0.890    0.785
##   SubNorms_cfa =~
##     SN1               1.000                               0.980    0.796
##     SN2               0.982    0.045   21.710    0.000    0.962    0.715
##     SN3               0.953    0.039   24.538    0.000    0.934    0.794
##   PBC_cfa =~
##     PBC1              1.000                               0.972    0.757
##     PBC2              1.284    0.062   20.627    0.000    1.248    0.773
##     PBC3              1.111    0.060   18.474    0.000    1.080    0.733
##     PBC4              1.225    0.064   19.156    0.000    1.190    0.769
##     PBC6              0.869    0.049   17.599    0.000    0.845    0.730
##   Intention_cfa =~
##     Int1              1.000                               1.139    0.872
##     Int2              1.033    0.035   29.139    0.000    1.177    0.870
##     Int3              1.130    0.039   29.203    0.000    1.287    0.909
##
## Covariances:
##                  Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##   Attitude_cfa ~~
##     SubNorms_cfa      0.675    0.050   13.525    0.000    0.787    0.787
##     PBC_cfa           0.619    0.051   12.219    0.000    0.728    0.728
##   SubNorms_cfa ~~
##     PBC_cfa           0.751    0.061   12.281    0.000    0.789    0.789
##   Attitude_cfa ~~
##     Intention_cfa     0.658    0.055   11.997    0.000    0.659    0.659
##   SubNorms_cfa ~~
##     Intention_cfa     0.823    0.066   12.519    0.000    0.737    0.737
##   PBC_cfa ~~
##     Intention_cfa     0.933    0.076   12.332    0.000    0.842    0.842
##
## Intercepts:
##                  Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##    .Att1              5.953    0.035  167.830    0.000    5.953    5.533
##    .Att2              5.901    0.036  163.840    0.000    5.901    5.402
##    .Att3              5.658    0.041  137.014    0.000    5.658    4.517
##    .Att4              5.946    0.036  163.500    0.000    5.946    5.390
##    .Att5              5.890    0.037  157.626    0.000    5.890    5.197
##    .SN1               5.555    0.041  136.932    0.000    5.555    4.515
```

```
##    .SN2           5.400    0.044  121.759    0.000    5.400    4.014
##    .SN3           5.679    0.039  146.594    0.000    5.679    4.833
##    .PBC1          5.654    0.042  133.513    0.000    5.654    4.402
##    .PBC2          4.977    0.053   93.458    0.000    4.977    3.081
##    .PBC3          5.171    0.049  106.417    0.000    5.171    3.508
##    .PBC4          5.114    0.051  100.242    0.000    5.114    3.305
##    .PBC6          5.793    0.038  151.806    0.000    5.793    5.005
##    .Int1          5.526    0.043  128.265    0.000    5.526    4.229
##    .Int2          5.407    0.045  121.282    0.000    5.407    3.999
##    .Int3          5.389    0.047  115.376    0.000    5.389    3.804
##     Attitude_cfa     0.000                            0.000    0.000
##     SubNorms_cfa     0.000                            0.000    0.000
##     PBC_cfa          0.000                            0.000    0.000
##     Intention_cfa    0.000                            0.000    0.000
##
## Variances:
##                  Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##    .Att1          0.391    0.047    8.325    0.000    0.391    0.338
##    .Att2          0.428    0.045    9.461    0.000    0.428    0.359
##    .Att3          0.526    0.049   10.769    0.000    0.526    0.335
##    .Att4          0.349    0.045    7.838    0.000    0.349    0.287
##    .Att5          0.493    0.061    8.033    0.000    0.493    0.384
##    .SN1           0.555    0.053   10.445    0.000    0.555    0.366
##    .SN2           0.884    0.101    8.735    0.000    0.884    0.489
##    .SN3           0.509    0.057    8.905    0.000    0.509    0.369
##    .PBC1          0.706    0.056   12.566    0.000    0.706    0.428
##    .PBC2          1.052    0.084   12.512    0.000    1.052    0.403
##    .PBC3          1.006    0.087   11.551    0.000    1.006    0.463
##    .PBC4          0.977    0.085   11.550    0.000    0.977    0.408
##    .PBC6          0.626    0.047   13.240    0.000    0.626    0.467
##    .Int1          0.409    0.047    8.659    0.000    0.409    0.240
##    .Int2          0.444    0.047    9.361    0.000    0.444    0.243
##    .Int3          0.349    0.044    7.872    0.000    0.349    0.174
##     Attitude_cfa     0.766    0.067   11.365    0.000    1.000    1.000
##     SubNorms_cfa     0.960    0.081   11.780    0.000    1.000    1.000
##     PBC_cfa          0.944    0.090   10.470    0.000    1.000    1.000
##     Intention_cfa    1.298    0.097   13.395    0.000    1.000    1.000
##
## R-Square:
##                  Estimate
##     Att1          0.662
##     Att2          0.641
##     Att3          0.665
##     Att4          0.713
##     Att5          0.616
##     SN1           0.634
```

```
## SN2 0.511
## SN3 0.631
## PBC1 0.572
## PBC2 0.597
## PBC3 0.537
## PBC4 0.592
## PBC6 0.533
## Int1 0.760
## Int2 0.757
## Int3 0.826
```

APPENDIX C: THEORY OF PLANNED BEHAVIOR SEM MODEL - INDIA

```
## lavaan 0.6-11 ended normally after 33 iterations
##
##   Estimator                                         ML
##   Optimization method                           NLMINB
##   Number of model parameters                        38
##
##   Number of observations                           920
##
## Model Test User Model:
##
##   Test statistic                               443.524
##   Degrees of freedom                                98
##   P-value (Chi-square)                           0.000
##
## Model Test Baseline Model:
##
##   Test statistic                             10105.973
##   Degrees of freedom                               120
##   P-value                                        0.000
##
## User Model versus Baseline Model:
##
##   Comparative Fit Index (CFI)                    0.965
##   Tucker-Lewis Index (TLI)                       0.958
##
## Loglikelihood and Information Criteria:
##
##   Loglikelihood user model (H0)             -19652.593
##   Loglikelihood unrestricted model (H1)             NA
##
##   Akaike (AIC)                               39381.186
##   Bayesian (BIC)                             39564.512
##   Sample-size adjusted Bayesian (BIC)        39443.829
##
## Root Mean Square Error of Approximation:
##
##   RMSEA                                          0.062
##   90 Percent confidence interval - lower         0.056
##   90 Percent confidence interval - upper         0.068
##   P-value RMSEA <= 0.05                          0.000
##
## Standardized Root Mean Square Residual:
##
##   SRMR                                           0.039
```

```
##
## Parameter Estimates:
##
##   Standard errors                          Standard
##   Information                              Expected
##   Information saturated (h1) model       Structured
##
## Latent Variables:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##   Attitude_cfa_IND =~
##     Att1              0.875    0.030   29.275    0.000    0.875    0.813
##     Att2              0.875    0.031   28.587    0.000    0.875    0.801
##     Att3              1.021    0.035   29.377    0.000    1.021    0.815
##     Att4              0.931    0.030   31.009    0.000    0.931    0.844
##     Att5              0.890    0.032   27.771    0.000    0.890    0.785
##   SubNorms_cfa_IND =~
##     SN1               0.980    0.036   27.415    0.000    0.980    0.797
##     SN2               0.961    0.041   23.608    0.000    0.961    0.715
##     SN3               0.933    0.034   27.308    0.000    0.933    0.794
##   PBC_cfa_IND =~
##     PBC1              0.974    0.037   26.187    0.000    0.974    0.758
##     PBC2              1.251    0.046   27.008    0.000    1.251    0.775
##     PBC3              1.077    0.043   24.885    0.000    1.077    0.731
##     PBC4              1.188    0.045   26.678    0.000    1.188    0.768
##     PBC6              0.844    0.034   24.783    0.000    0.844    0.729
##   Intention_cfa_IND =~
##     Int1              0.609    0.025   23.959    0.000    1.149    0.871
##     Int2              0.617    0.026   23.722    0.000    1.163    0.860
##     Int3              0.687    0.028   24.620    0.000    1.296    0.908
##
## Regressions:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##   Intention_cfa_IND ~
##     Attitud_cf_IND    0.027    0.088    0.302    0.763    0.014    0.014
##     SubNrms_cf_IND    0.316    0.112    2.829    0.005    0.168    0.168
##     PBC_cfa_IND       1.317    0.118   11.171    0.000    0.698    0.698
##
## Covariances:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##   Attitude_cfa_IND ~~
##     SubNrms_cf_IND    0.787    0.019   42.214    0.000    0.787    0.787
##     PBC_cfa_IND       0.728    0.020   36.397    0.000    0.728    0.728
##   SubNorms_cfa_IND ~~
##     PBC_cfa_IND       0.788    0.020   40.313    0.000    0.788    0.788
##
## Variances:
```

```
##               Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##    .Att1           0.392    0.022   17.647    0.000    0.392    0.338
##    .Att2           0.428    0.024   17.981    0.000    0.428    0.359
##    .Att3           0.526    0.030   17.594    0.000    0.526    0.335
##    .Att4           0.349    0.021   16.611    0.000    0.349    0.287
##    .Att5           0.492    0.027   18.332    0.000    0.492    0.383
##    .SN1            0.553    0.036   15.586    0.000    0.553    0.365
##    .SN2            0.886    0.049   18.004    0.000    0.886    0.489
##    .SN3            0.510    0.032   15.678    0.000    0.510    0.369
##    .PBC1           0.702    0.038   18.313    0.000    0.702    0.425
##    .PBC2           1.044    0.058   17.960    0.000    1.044    0.400
##    .PBC3           1.011    0.054   18.793    0.000    1.011    0.466
##    .PBC4           0.982    0.054   18.107    0.000    0.982    0.410
##    .PBC6           0.628    0.033   18.827    0.000    0.628    0.469
##    .Int1           0.420    0.027   15.734    0.000    0.420    0.241
##    .Int2           0.475    0.029   16.301    0.000    0.475    0.260
##    .Int3           0.356    0.028   12.939    0.000    0.356    0.175
##     Attitud_cf_IND    1.000                               1.000    1.000
##     SubNrms_cf_IND    1.000                               1.000    1.000
##     PBC_cfa_IND       1.000                               1.000    1.000
##    .Intentn_cf_IND    1.000                               0.281    0.281
##
## R-Square:
##               Estimate
##     Att1           0.662
##     Att2           0.641
##     Att3           0.665
##     Att4           0.713
##     Att5           0.617
##     SN1            0.635
##     SN2            0.511
##     SN3            0.631
##     PBC1           0.575
##     PBC2           0.600
##     PBC3           0.534
##     PBC4           0.590
##     PBC6           0.531
##     Int1           0.759
##     Int2           0.740
##     Int3           0.825
##     Intentn_cf_IND    0.719
```

APPENDIX D: THEORY OF PLANNED BEHAVIOR SEM MODEL - USA

```
## lavaan 0.6-11 ended normally after 35 iterations
##
##   Estimator                                   ML
##   Optimization method                     NLMINB
##   Number of model parameters                  38
##
##   Number of observations                     900
##
## Model Test User Model:
##
##   Test statistic                         912.975
##   Degrees of freedom                          98
##   P-value (Chi-square)                     0.000
##
## Model Test Baseline Model:
##
##   Test statistic                       12813.915
##   Degrees of freedom                         120
##   P-value                                  0.000
##
## User Model versus Baseline Model:
##
##   Comparative Fit Index (CFI)              0.936
##   Tucker-Lewis Index (TLI)                 0.921
##
## Loglikelihood and Information Criteria:
##
##   Loglikelihood user model (H0)       -21363.353
##   Loglikelihood unrestricted model (H1)      NA
##
##   Akaike (AIC)                         42802.706
##   Bayesian (BIC)                       42985.197
##   Sample-size adjusted Bayesian (BIC)  42864.515
##
## Root Mean Square Error of Approximation:
##
##   RMSEA                                    0.096
##   90 Percent confidence interval - lower   0.090
##   90 Percent confidence interval - upper   0.102
##   P-value RMSEA <= 0.05                    0.000
##
## Standardized Root Mean Square Residual:
##
##   SRMR                                     0.093
```

```
##
## Parameter Estimates:
##
##   Standard errors                        Standard
##   Information                            Expected
##   Information saturated (h1) model       Structured
##
## Latent Variables:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##   Attitude_cfa_USA =~
##     Att1              1.223    0.036   33.899    0.000    1.223    0.888
##     Att2              1.269    0.037   34.304    0.000    1.269    0.894
##     Att3              1.308    0.037   35.142    0.000    1.308    0.907
##     Att4              1.320    0.036   36.458    0.000    1.320    0.926
##     Att5              1.310    0.038   34.641    0.000    1.310    0.900
##   SubNorms_cfa_USA =~
##     SN1               1.417    0.043   32.848    0.000    1.417    0.887
##     SN2               1.422    0.048   29.646    0.000    1.422    0.830
##     SN3               1.259    0.042   29.888    0.000    1.259    0.835
##   PBC_cfa_USA =~
##     PBC1              1.143    0.052   21.803    0.000    1.143    0.679
##     PBC2              1.429    0.057   24.876    0.000    1.429    0.749
##     PBC3              1.290    0.052   25.015    0.000    1.290    0.752
##     PBC4              1.308    0.054   24.086    0.000    1.308    0.731
##     PBC6              0.913    0.048   19.075    0.000    0.913    0.611
##   Intention_cfa_USA =~
##     Int1              0.906    0.034   26.474    0.000    1.558    0.845
##     Int2              0.982    0.033   29.961    0.000    1.688    0.944
##     Int3              0.986    0.033   30.068    0.000    1.695    0.949
##
## Regressions:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##   Intention_cfa_USA ~
##     Attitud_cf_USA    0.051    0.057    0.888    0.375    0.029    0.029
##     SubNrms_cf_USA    0.619    0.074    8.362    0.000    0.360    0.360
##     PBC_cfa_USA       0.879    0.074   11.948    0.000    0.511    0.511
##
## Covariances:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##   Attitude_cfa_USA ~~
##     SubNrms_cf_USA    0.671    0.021   31.686    0.000    0.671    0.671
##     PBC_cfa_USA       0.524    0.028   18.579    0.000    0.524    0.524
##   SubNorms_cfa_USA ~~
##     PBC_cfa_USA       0.653    0.025   26.482    0.000    0.653    0.653
##
## Variances:
```

```
##              Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##   .Att1           0.401    0.023   17.756    0.000    0.401    0.211
##   .Att2           0.403    0.023   17.507    0.000    0.403    0.200
##   .Att3           0.368    0.022   16.895    0.000    0.368    0.177
##   .Att4           0.288    0.019   15.577    0.000    0.288    0.142
##   .Att5           0.405    0.023   17.278    0.000    0.405    0.191
##   .SN1            0.542    0.042   12.757    0.000    0.542    0.213
##   .SN2            0.910    0.056   16.130    0.000    0.910    0.310
##   .SN3            0.689    0.043   15.937    0.000    0.689    0.303
##   .PBC1           1.528    0.083   18.426    0.000    1.528    0.539
##   .PBC2           1.602    0.094   17.028    0.000    1.602    0.440
##   .PBC3           1.281    0.076   16.949    0.000    1.281    0.435
##   .PBC4           1.488    0.085   17.446    0.000    1.488    0.465
##   .PBC6           1.398    0.073   19.277    0.000    1.398    0.626
##   .Int1           0.976    0.052   18.630    0.000    0.976    0.287
##   .Int2           0.346    0.030   11.510    0.000    0.346    0.108
##   .Int3           0.318    0.029   10.775    0.000    0.318    0.100
##    Attitud_cf_USA    1.000                               1.000    1.000
##    SubNrms_cf_USA    1.000                               1.000    1.000
##    PBC_cfa_USA       1.000                               1.000    1.000
##   .Intentn_cf_USA    1.000                               0.338    0.338
##
## R-Square:
##              Estimate
##    Att1           0.789
##    Att2           0.800
##    Att3           0.823
##    Att4           0.858
##    Att5           0.809
##    SN1            0.787
##    SN2            0.690
##    SN3            0.697
##    PBC1           0.461
##    PBC2           0.560
##    PBC3           0.565
##    PBC4           0.535
##    PBC6           0.374
##    Int1           0.713
##    Int2           0.892
##    Int3           0.900
##    Intentn_cf_USA    0.662
```

APPENDIX E: VALUE-BELIEF-NORM THEORY SEM MODEL - INDIA

```
## lavaan 0.6-11 ended normally after 61 iterations
##
##   Estimator                                         ML
##   Optimization method                           NLMINB
##   Number of model parameters                       120
##
##   Number of observations                           920
##
## Model Test User Model:
##
##   Test statistic                              1316.455
##   Degrees of freedom                               509
##   P-value (Chi-square)                           0.000
##
## Model Test Baseline Model:
##
##   Test statistic                             11387.171
##   Degrees of freedom                               561
##   P-value                                        0.000
##
## User Model versus Baseline Model:
##
##   Comparative Fit Index (CFI)                    0.925
##   Tucker-Lewis Index (TLI)                       0.918
##
## Loglikelihood and Information Criteria:
##
##   Loglikelihood user model (H0)             -45394.886
##   Loglikelihood unrestricted model (H1)             NA
##
##   Akaike (AIC)                               91029.771
##   Bayesian (BIC)                             91608.696
##   Sample-size adjusted Bayesian (BIC)        91227.590
##
## Root Mean Square Error of Approximation:
##
##   RMSEA                                          0.042
##   90 Percent confidence interval - lower         0.039
##   90 Percent confidence interval - upper         0.044
##   P-value RMSEA <= 0.05                          1.000
##
## Standardized Root Mean Square Residual:
##
##   SRMR                                           0.077
```

```
##
## Parameter Estimates:
##
##   Standard errors                         Standard
##   Information                             Expected
##   Information saturated (h1) model        Structured
##
## Latent Variables:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##   BioVal_cfa =~
##     BioV1             0.551    0.028   19.457    0.000    0.551    0.625
##     BioV2             0.516    0.021   24.028    0.000    0.516    0.736
##     BioV3             0.446    0.019   23.064    0.000    0.446    0.714
##     BioV4             0.616    0.024   25.880    0.000    0.616    0.778
##   AltVal_cfa =~
##     AltV1             0.534    0.030   17.772    0.000    0.534    0.602
##     AltV3             0.615    0.039   15.919    0.000    0.615    0.547
##     AltV4             0.589    0.035   16.765    0.000    0.589    0.572
##     AltV5             0.509    0.030   16.973    0.000    0.509    0.579
##   EgoVal_cfa =~
##     EgoV1             1.482    0.072   20.583    0.000    1.482    0.814
##     EgoV2             1.332    0.070   18.920    0.000    1.332    0.724
##   EnviroConcern =~
##     Nep3              0.439    0.036   12.251    0.000    0.642    0.534
##     Nep5              0.373    0.035   10.620    0.000    0.545    0.453
##     Nep9              0.418    0.036   11.579    0.000    0.611    0.495
##     Nep15             0.427    0.035   12.284    0.000    0.623    0.542
##   Anthropocentric =~
##     Nep2              1.064    0.066   16.168    0.000    1.319    0.659
##     Nep8              0.874    0.058   15.056    0.000    1.083    0.579
##     Nep10             0.725    0.062   11.667    0.000    0.898    0.489
##     Nep12             1.080    0.065   16.730    0.000    1.339    0.652
##     Nep14             0.573    0.050   11.372    0.000    0.710    0.444
##   AwareCon_cfa =~
##     AC1               0.403    0.034   11.732    0.000    0.725    0.665
##     AC2               0.411    0.034   11.964    0.000    0.739    0.705
##     AC3               0.364    0.034   10.581    0.000    0.655    0.530
##     AC4               0.358    0.032   11.242    0.000    0.644    0.599
##   AscResp_cfa =~
##     AR1               0.472    0.028   16.801    0.000    0.699    0.727
##     AR2               0.452    0.028   16.293    0.000    0.669    0.687
##     AR3               0.505    0.036   14.066    0.000    0.747    0.566
##   PersNorm_cfa =~
##     PN1               0.773    0.034   22.424    0.000    0.989    0.764
##     PN2               0.801    0.043   18.634    0.000    1.024    0.641
##     PN3               0.721    0.036   19.782    0.000    0.922    0.678
```

```
##    PN4            0.642   0.031   20.982   0.000   0.821   0.723
##    PN5            0.603   0.030   20.307   0.000   0.771   0.702
##   Intent_cfa =~
##    Int1           0.766   0.029   26.059   0.000   1.157   0.877
##    Int2           0.772   0.030   25.649   0.000   1.167   0.863
##    Int3           0.850   0.032   26.627   0.000   1.284   0.900
##
## Regressions:
##                Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##   EnviroConcern ~
##    BioVal_cfa      -0.017   0.148   -0.112   0.911   -0.011   -0.011
##    AltVal_cfa       1.082   0.190    5.688   0.000    0.741    0.741
##    EgoVal_cfa      -0.208   0.066   -3.161   0.002   -0.142   -0.142
##   Anthropocentric ~
##    BioVal_cfa      -0.191   0.117   -1.625   0.104   -0.154   -0.154
##    AltVal_cfa       0.353   0.124    2.855   0.004    0.285    0.285
##    EgoVal_cfa      -0.719   0.067  -10.752   0.000   -0.580   -0.580
##   AwareCon_cfa ~
##    Anthropocentrc   -0.222   0.061   -3.664   0.000   -0.153   -0.153
##    EnviroConcern     1.035   0.126    8.224   0.000    0.840    0.840
##   AscResp_cfa ~
##    AwareCon_cfa     0.607   0.065    9.334   0.000    0.738    0.738
##   PersNorm_cfa ~
##    AscResp_cfa      0.538   0.046   11.779   0.000    0.623    0.623
##   Intent_cfa ~
##    PersNorm_cfa     0.885   0.057   15.590   0.000    0.750    0.750
##
## Covariances:
##                Estimate  Std.Err  z-value  P(>|z|)  Std.lv  Std.all
##  .PN4 ~~
##   .PN5          0.161    0.027    5.928   0.000    0.161    0.262
##  .Nep2 ~~
##   .Nep10        -0.507   0.103   -4.926   0.000   -0.507   -0.210
##  .Nep10 ~~
##   .Nep14         0.390   0.093    4.217   0.000    0.390    0.170
##  .Nep5 ~~
##   .Nep15         0.188   0.040    4.651   0.000    0.188    0.181
##   BioVal_cfa ~~
##    AltVal_cfa      0.805   0.026   30.852   0.000    0.805    0.805
##    EgoVal_cfa      0.098   0.042    2.353   0.019    0.098    0.098
##   AltVal_cfa ~~
##    EgoVal_cfa      0.117   0.046    2.549   0.011    0.117    0.117
##
## Intercepts:
##                Estimate  Std.Err  z-value  P(>|z|)  Std.lv  Std.all
##   .BioV1         6.482    0.029  222.897   0.000    6.482    7.349
```

```
##    .BioV2          6.583    0.023  284.938    0.000    6.583    9.394
##    .BioV3          6.655    0.021  322.812    0.000    6.655   10.643
##    .BioV4          6.462    0.026  247.565    0.000    6.462    8.162
##    .AltV1          6.362    0.029  217.755    0.000    6.362    7.179
##    .AltV3          6.108    0.037  164.955    0.000    6.108    5.438
##    .AltV4          6.292    0.034  185.649    0.000    6.292    6.121
##    .AltV5          6.247    0.029  215.531    0.000    6.247    7.106
##    .EgoV1          4.342    0.060   72.324    0.000    4.342    2.384
##    .EgoV2          4.086    0.061   67.424    0.000    4.086    2.223
##    .Nep3           6.042    0.040  152.582    0.000    6.042    5.030
##    .Nep5           6.075    0.040  153.033    0.000    6.075    5.045
##    .Nep9           5.807    0.041  142.793    0.000    5.807    4.708
##    .Nep15          6.036    0.038  159.386    0.000    6.036    5.255
##    .Nep2           4.615    0.066   69.957    0.000    4.615    2.306
##    .Nep8           3.918    0.062   63.482    0.000    3.918    2.093
##    .Nep10          3.378    0.061   55.795    0.000    3.378    1.839
##    .Nep12          4.867    0.068   71.947    0.000    4.867    2.372
##    .Nep14          2.917    0.053   55.370    0.000    2.917    1.825
##    .AC1            6.180    0.036  171.861    0.000    6.180    5.666
##    .AC2            5.971    0.035  172.775    0.000    5.971    5.696
##    .AC3            5.808    0.041  142.422    0.000    5.808    4.696
##    .AC4            5.633    0.035  158.994    0.000    5.633    5.242
##    .AR1            6.177    0.032  194.879    0.000    6.177    6.425
##    .AR2            6.162    0.032  192.073    0.000    6.162    6.332
##    .AR3            5.571    0.044  127.896    0.000    5.571    4.217
##    .PN1            5.564    0.043  130.341    0.000    5.564    4.297
##    .PN2            5.166    0.053   98.010    0.000    5.166    3.231
##    .PN3            5.376    0.045  119.815    0.000    5.376    3.950
##    .PN4            5.878    0.037  157.000    0.000    5.878    5.176
##    .PN5            6.014    0.036  166.002    0.000    6.014    5.473
##    .Int1           5.518    0.043  126.931    0.000    5.518    4.185
##    .Int2           5.407    0.045  121.276    0.000    5.407    3.998
##    .Int3           5.382    0.047  114.391    0.000    5.382    3.771
##     BioVal_cfa     0.000                               0.000    0.000
##     AltVal_cfa     0.000                               0.000    0.000
##     EgoVal_cfa     0.000                               0.000    0.000
##    .EnviroConcern  0.000                               0.000    0.000
##    .Anthropocentrc 0.000                               0.000    0.000
##    .AwareCon_cfa   0.000                               0.000    0.000
##    .AscResp_cfa    0.000                               0.000    0.000
##    .PersNorm_cfa   0.000                               0.000    0.000
##    .Intent_cfa     0.000                               0.000    0.000
##
## Variances:
##                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##    .BioV1          0.474    0.025   18.793    0.000    0.474    0.610
```

```
##    .BioV2           0.225    0.014   16.463    0.000    0.225    0.458
##    .BioV3           0.192    0.011   17.090    0.000    0.192    0.491
##    .BioV4           0.247    0.017   14.972    0.000    0.247    0.394
##    .AltV1           0.501    0.028   17.981    0.000    0.501    0.638
##    .AltV3           0.883    0.047   18.886    0.000    0.883    0.700
##    .AltV4           0.711    0.038   18.506    0.000    0.711    0.672
##    .AltV5           0.514    0.028   18.404    0.000    0.514    0.665
##    .EgoV1           1.119    0.165    6.796    0.000    1.119    0.337
##    .EgoV2           1.605    0.147   10.944    0.000    1.605    0.475
##    .Nep3            1.031    0.055   18.610    0.000    1.031    0.715
##    .Nep5            1.152    0.059   19.415    0.000    1.152    0.795
##    .Nep9            1.148    0.060   19.149    0.000    1.148    0.755
##    .Nep15           0.931    0.051   18.305    0.000    0.931    0.706
##    .Nep2            2.264    0.152   14.865    0.000    2.264    0.565
##    .Nep8            2.332    0.131   17.755    0.000    2.332    0.665
##    .Nep10           2.566    0.144   17.811    0.000    2.566    0.761
##    .Nep12           2.418    0.153   15.836    0.000    2.418    0.574
##    .Nep14           2.050    0.106   19.397    0.000    2.050    0.802
##    .AC1             0.664    0.038   17.350    0.000    0.664    0.558
##    .AC2             0.552    0.034   16.319    0.000    0.552    0.503
##    .AC3             1.101    0.057   19.452    0.000    1.101    0.720
##    .AC4             0.740    0.040   18.563    0.000    0.740    0.641
##    .AR1             0.436    0.030   14.724    0.000    0.436    0.471
##    .AR2             0.499    0.031   16.069    0.000    0.499    0.527
##    .AR3             1.187    0.064   18.673    0.000    1.187    0.680
##    .PN1             0.699    0.043   16.341    0.000    0.699    0.417
##    .PN2             1.507    0.080   18.942    0.000    1.507    0.590
##    .PN3             1.001    0.054   18.378    0.000    1.001    0.541
##    .PN4             0.616    0.036   17.088    0.000    0.616    0.478
##    .PN5             0.613    0.035   17.494    0.000    0.613    0.507
##    .Int1            0.400    0.027   14.614    0.000    0.400    0.230
##    .Int2            0.468    0.030   15.560    0.000    0.468    0.256
##    .Int3            0.386    0.030   12.782    0.000    0.386    0.190
##     BioVal_cfa      1.000                               1.000    1.000
##     AltVal_cfa      1.000                               1.000    1.000
##     EgoVal_cfa      1.000                               1.000    1.000
##    .EnviroConcern   1.000                               0.469    0.469
##    .Anthropocentrc  1.000                               0.650    0.650
##    .AwareCon_cfa    1.000                               0.309    0.309
##    .AscResp_cfa     1.000                               0.456    0.456
##    .PersNorm_cfa    1.000                               0.611    0.611
##    .Intent_cfa      1.000                               0.438    0.438
##
## R-Square:
##                    Estimate
##     BioV1           0.390
```

```
## BioV2 0.542
## BioV3 0.509
## BioV4 0.606
## AltV1 0.362
## AltV3 0.300
## AltV4 0.328
## AltV5 0.335
## EgoV1 0.663
## EgoV2 0.525
## Nep3 0.285
## Nep5 0.205
## Nep9 0.245
## Nep15 0.294
## Nep2 0.435
## Nep8 0.335
## Nep10 0.239
## Nep12 0.426
## Nep14 0.198
## AC1 0.442
## AC2 0.497
## AC3 0.280
## AC4 0.359
## AR1 0.529
## AR2 0.473
## AR3 0.320
## PN1 0.583
## PN2 0.410
## PN3 0.459
## PN4 0.522
## PN5 0.493
## Int1 0.770
## Int2 0.744
## Int3 0.810
## EnviroConcern 0.531
## Anthropocentrc 0.350
## AwareCon_cfa 0.691
## AscResp_cfa 0.544
## PersNorm_cfa 0.389
## Intent_cfa 0.562
```

APPENDIX F: VALUE-BELIEF-NORM THEORY SEM MODEL – USA

```
## lavaan 0.6-11 ended normally after 51 iterations
##
##   Estimator                                         ML
##   Optimization method                           NLMINB
##   Number of model parameters                       126
##
##   Number of observations                           900
##
## Model Test User Model:
##
##   Test statistic                              2214.262
##   Degrees of freedom                               576
##   P-value (Chi-square)                           0.000
##
## Model Test Baseline Model:
##
##   Test statistic                             19154.477
##   Degrees of freedom                               630
##   P-value                                        0.000
##
## User Model versus Baseline Model:
##
##   Comparative Fit Index (CFI)                    0.912
##   Tucker-Lewis Index (TLI)                       0.903
##
## Loglikelihood and Information Criteria:
##
##   Loglikelihood user model (H0)             -50807.926
##   Loglikelihood unrestricted model (H1)             NA
##
##   Akaike (AIC)                              101867.853
##   Bayesian (BIC)                            102472.954
##   Sample-size adjusted Bayesian (BIC)       102072.799
##
## Root Mean Square Error of Approximation:
##
##   RMSEA                                          0.056
##   90 Percent confidence interval - lower         0.054
##   90 Percent confidence interval - upper         0.059
##   P-value RMSEA <= 0.05                          0.000
##
## Standardized Root Mean Square Residual:
##
```

```
##   SRMR                          0.109
##
## Parameter Estimates:
##
##   Standard errors                          Standard
##   Information                              Expected
##   Information saturated (h1) model       Structured
##
## Latent Variables:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##   BioVal_cfa =~
##     BioV1           1.103    0.039   28.024    0.000    1.103    0.801
##     BioV2           1.096    0.037   29.724    0.000    1.096    0.833
##     BioV3           0.865    0.033   26.134    0.000    0.865    0.763
##     BioV4           1.126    0.043   25.980    0.000    1.126    0.760
##   AltVal_cfa =~
##     AltV1           0.716    0.040   17.842    0.000    0.716    0.594
##     AltV2           1.022    0.043   23.670    0.000    1.022    0.737
##     AltV3           0.715    0.036   20.040    0.000    0.715    0.650
##     AltV4           0.702    0.044   16.055    0.000    0.702    0.540
##     AltV5           0.889    0.037   24.306    0.000    0.889    0.752
##   EgoVal_cfa =~
##     EgoV1           1.345    0.056   24.109    0.000    1.345    0.779
##     EgoV2           1.409    0.052   26.879    0.000    1.409    0.860
##     EgoV3           0.968    0.060   16.009    0.000    0.968    0.540
##   EnviroConcern =~
##     Nep3            0.600    0.033   18.156    0.000    0.895    0.683
##     Nep5            0.720    0.036   19.930    0.000    1.074    0.762
##     Nep13           0.645    0.036   17.844    0.000    0.963    0.670
##     Nep15           0.818    0.040   20.456    0.000    1.221    0.773
##   Anthropocentric =~
##     Nep2            0.867    0.051   17.136    0.000    1.212    0.690
##     Nep8            0.858    0.049   17.433    0.000    1.200    0.706
##     Nep10           0.819    0.052   15.745    0.000    1.145    0.607
##     Nep12           0.848    0.055   15.281    0.000    1.185    0.601
##     Nep14           0.663    0.049   13.634    0.000    0.927    0.529
##   AwareCon_cfa =~
##     AC1             0.682    0.032   21.112    0.000    0.948    0.781
##     AC2             0.643    0.031   20.749    0.000    0.894    0.764
##     AC3             0.489    0.034   14.311    0.000    0.680    0.520
##     AC4             0.514    0.032   15.910    0.000    0.716    0.578
##   AscResp_cfa =~
##     AR1             0.941    0.047   20.016    0.000    1.239    0.747
##     AR2             0.717    0.040   18.046    0.000    0.944    0.655
##     AR3             0.866    0.047   18.358    0.000    1.140    0.689
##   PersNorm_cfa =~
```

```
##    PN1            0.917   0.045   20.567   0.000   1.555   0.895
##    PN2            0.922   0.046   20.167   0.000   1.564   0.866
##    PN3            0.934   0.046   20.469   0.000   1.584   0.888
##    PN4            0.691   0.037   18.769   0.000   1.171   0.777
##    PN5            0.706   0.039   18.219   0.000   1.198   0.745
##   Intent_cfa =~
##    Int1           0.978   0.035   28.025   0.000   1.562   0.846
##    Int2           1.063   0.033   32.326   0.000   1.697   0.949
##    Int3           1.057   0.033   32.182   0.000   1.688   0.944
##
## Regressions:
##                Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##   EnviroConcern ~
##    BioVal_cfa       1.476    0.130   11.330    0.000    0.989    0.989
##    AltVal_cfa      -0.533    0.105   -5.095    0.000   -0.357   -0.357
##    EgoVal_cfa      -0.105    0.051   -2.070    0.038   -0.070   -0.070
##   Anthropocentric ~
##    BioVal_cfa       1.146    0.124    9.257    0.000    0.819    0.819
##    AltVal_cfa      -0.681    0.112   -6.093    0.000   -0.487   -0.487
##    EgoVal_cfa      -0.718    0.067  -10.682    0.000   -0.513   -0.513
##   AwareCon_cfa ~
##    Anthropocentrc   -0.094    0.038   -2.449    0.014   -0.094   -0.094
##    EnviroConcern     0.674    0.052   12.893    0.000    0.723    0.723
##   AscResp_cfa ~
##    AwareCon_cfa      0.616    0.049   12.677    0.000    0.651    0.651
##   PersNorm_cfa ~
##    AscResp_cfa       1.040    0.080   12.937    0.000    0.808    0.808
##   Intent_cfa ~
##    PersNorm_cfa      0.734    0.046   15.800    0.000    0.779    0.779
##
## Covariances:
##                Estimate  Std.Err  z-value  P(>|z|)  Std.lv  Std.all
##  .PN4 ~~
##   .PN5           0.558    0.044   12.762    0.000    0.558    0.548
##  .AltV1 ~~
##   .AltV3         0.335    0.035    9.562    0.000    0.335    0.412
##  .AR1 ~~
##   .AR3           0.470    0.072    6.507    0.000    0.470    0.356
##  .Nep15 ~~
##   .Nep10         0.410    0.062    6.650    0.000    0.410    0.273
##   BioVal_cfa ~~
##    AltVal_cfa      0.769    0.021   36.278    0.000    0.769    0.769
##    EgoVal_cfa      0.165    0.038    4.294    0.000    0.165    0.165
##   AltVal_cfa ~~
##    EgoVal_cfa      0.139    0.041    3.422    0.001    0.139    0.139
##
```

```
## Intercepts:
##                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##    .BioV1             5.497    0.046  119.667    0.000    5.497    3.989
##    .BioV2             5.586    0.044  127.259    0.000    5.586    4.242
##    .BioV3             5.954    0.038  157.677    0.000    5.954    5.256
##    .BioV4             5.119    0.049  103.632    0.000    5.119    3.454
##    .AltV1             5.926    0.040  147.344    0.000    5.926    4.911
##    .AltV2             5.171    0.046  111.969    0.000    5.171    3.732
##    .AltV3             6.093    0.037  166.093    0.000    6.093    5.536
##    .AltV4             5.852    0.043  134.947    0.000    5.852    4.498
##    .AltV5             5.737    0.039  145.648    0.000    5.737    4.855
##    .EgoV1             2.621    0.058   45.570    0.000    2.621    1.519
##    .EgoV2             2.511    0.055   45.952    0.000    2.511    1.532
##    .EgoV3             3.949    0.060   66.091    0.000    3.949    2.203
##    .Nep3              5.539    0.044  126.798    0.000    5.539    4.227
##    .Nep5              5.661    0.047  120.437    0.000    5.661    4.015
##    .Nep13             5.377    0.048  112.222    0.000    5.377    3.741
##    .Nep15             5.257    0.053   99.886    0.000    5.257    3.330
##    .Nep2              4.733    0.059   80.825    0.000    4.733    2.694
##    .Nep8              4.651    0.057   82.056    0.000    4.651    2.735
##    .Nep10             4.649    0.063   73.940    0.000    4.649    2.465
##    .Nep12             4.576    0.066   69.569    0.000    4.576    2.319
##    .Nep14             4.493    0.058   76.852    0.000    4.493    2.562
##    .AC1               5.699    0.040  140.898    0.000    5.699    4.697
##    .AC2               5.488    0.039  140.627    0.000    5.488    4.688
##    .AC3               5.261    0.044  120.791    0.000    5.261    4.026
##    .AC4               5.209    0.041  126.276    0.000    5.209    4.209
##    .AR1               4.512    0.055   81.615    0.000    4.512    2.720
##    .AR2               5.179    0.048  107.720    0.000    5.179    3.591
##    .AR3               4.293    0.055   77.866    0.000    4.293    2.596
##    .PN1               4.306    0.058   74.352    0.000    4.306    2.478
##    .PN2               3.636    0.060   60.409    0.000    3.636    2.014
##    .PN3               3.892    0.060   65.411    0.000    3.892    2.180
##    .PN4               4.989    0.050   99.265    0.000    4.989    3.309
##    .PN5               4.953    0.054   92.428    0.000    4.953    3.081
##    .Int1              3.944    0.062   64.095    0.000    3.944    2.137
##    .Int2              3.489    0.060   58.509    0.000    3.489    1.950
##    .Int3              3.350    0.060   56.221    0.000    3.350    1.874
##     BioVal_cfa        0.000                               0.000    0.000
##     AltVal_cfa        0.000                               0.000    0.000
##     EgoVal_cfa        0.000                               0.000    0.000
##    .EnviroConcern     0.000                               0.000    0.000
##    .Anthropocentrc    0.000                               0.000    0.000
##    .AwareCon_cfa      0.000                               0.000    0.000
##    .AscResp_cfa       0.000                               0.000    0.000
##    .PersNorm_cfa      0.000                               0.000    0.000
```

```
##   .Intent_cfa       0.000                          0.000    0.000
## Variances:
##                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##   .BioV1            0.681    0.040   17.031    0.000    0.681    0.359
##   .BioV2            0.532    0.033   15.910    0.000    0.532    0.307
##   .BioV3            0.536    0.030   17.961    0.000    0.536    0.417
##   .BioV4            0.927    0.051   18.026    0.000    0.927    0.422
##   .AltV1            0.943    0.050   18.685    0.000    0.943    0.648
##   .AltV2            0.876    0.055   15.999    0.000    0.876    0.456
##   .AltV3            0.700    0.039   17.929    0.000    0.700    0.578
##   .AltV4            1.200    0.062   19.455    0.000    1.200    0.709
##   .AltV5            0.606    0.039   15.499    0.000    0.606    0.434
##   .EgoV1            1.169    0.094   12.402    0.000    1.169    0.393
##   .EgoV2            0.702    0.089    7.863    0.000    0.702    0.261
##   .EgoV3            2.275    0.117   19.375    0.000    2.275    0.708
##   .Nep3             0.916    0.051   18.132    0.000    0.916    0.533
##   .Nep5             0.835    0.051   16.307    0.000    0.835    0.420
##   .Nep13            1.138    0.062   18.348    0.000    1.138    0.551
##   .Nep15            1.001    0.063   15.899    0.000    1.001    0.402
##   .Nep2             1.617    0.099   16.313    0.000    1.617    0.524
##   .Nep8             1.451    0.091   15.853    0.000    1.451    0.502
##   .Nep10            2.246    0.124   18.100    0.000    2.246    0.631
##   .Nep12            2.488    0.137   18.190    0.000    2.488    0.639
##   .Nep14            2.216    0.116   19.147    0.000    2.216    0.720
##   .AC1              0.573    0.040   14.310    0.000    0.573    0.389
##   .AC2              0.571    0.038   15.018    0.000    0.571    0.416
##   .AC3              1.245    0.063   19.627    0.000    1.245    0.729
##   .AC4              1.019    0.053   19.055    0.000    1.019    0.666
##   .AR1              1.215    0.086   14.095    0.000    1.215    0.442
##   .AR2              1.189    0.068   17.465    0.000    1.189    0.572
##   .AR3              1.436    0.092   15.681    0.000    1.436    0.525
##   .PN1              0.601    0.039   15.268    0.000    0.601    0.199
##   .PN2              0.815    0.049   16.793    0.000    0.815    0.250
##   .PN3              0.677    0.043   15.726    0.000    0.677    0.212
##   .PN4              0.901    0.048   18.959    0.000    0.901    0.396
##   .PN5              1.150    0.059   19.336    0.000    1.150    0.445
##   .Int1             0.969    0.052   18.561    0.000    0.969    0.284
##   .Int2             0.320    0.030   10.613    0.000    0.320    0.100
##   .Int3             0.347    0.031   11.341    0.000    0.347    0.109
##    BioVal_cfa       1.000                               1.000    1.000
##    AltVal_cfa       1.000                               1.000    1.000
##    EgoVal_cfa       1.000                               1.000    1.000
##   .EnviroConcern    1.000                               0.449    0.449
##   .Anthropocentrc   1.000                               0.511    0.511
##   .AwareCon_cfa     1.000                               0.517    0.517
##   .AscResp_cfa      1.000                               0.577    0.577
```

```
##    .PersNorm_cfa     1.000                             0.348    0.348
##    .Intent_cfa       1.000                             0.392    0.392
##
## R-Square:
##                    Estimate
##     BioV1          0.641
##     BioV2          0.693
##     BioV3          0.583
##     BioV4          0.578
##     AltV1          0.352
##     AltV2          0.544
##     AltV3          0.422
##     AltV4          0.291
##     AltV5          0.566
##     EgoV1          0.607
##     EgoV2          0.739
##     EgoV3          0.292
##     Nep3           0.467
##     Nep5           0.580
##     Nep13          0.449
##     Nep15          0.598
##     Nep2           0.476
##     Nep8           0.498
##     Nep10          0.369
##     Nep12          0.361
##     Nep14          0.280
##     AC1            0.611
##     AC2            0.584
##     AC3            0.271
##     AC4            0.334
##     AR1            0.558
##     AR2            0.428
##     AR3            0.475
##     PN1            0.801
##     PN2            0.750
##     PN3            0.788
##     PN4            0.604
##     PN5            0.555
##     Int1           0.716
##     Int2           0.900
##     Int3           0.891
##     EnviroConcern    0.551
##     Anthropocentrc   0.489
##     AwareCon_cfa     0.483
##     AscResp_cfa      0.423
##     PersNorm_cfa     0.652
```

Intent_cfa 0.608

APPENDIX G: VBN SEM WITH WILDLIFE VALUE ORIENTATIONS - USA

```
## lavaan 0.6-11 ended normally after 45 iterations
##
##   Estimator                          ML
##   Optimization method            NLMINB
##   Number of model parameters        123
##
##   Number of observations            900
##
## Model Test User Model:
##
##   Test statistic               2479.781
##   Degrees of freedom                579
##   P-value (Chi-square)            0.000
##
## Model Test Baseline Model:
##
##   Test statistic              21071.551
##   Degrees of freedom                630
##   P-value                         0.000
##
## User Model versus Baseline Model:
##
##   Comparative Fit Index (CFI)     0.907
##   Tucker-Lewis Index (TLI)        0.899
##
## Loglikelihood and Information Criteria:
##
##   Loglikelihood user model (H0)     -49479.905
##   Loglikelihood unrestricted model (H1)     NA
##
##   Akaike (AIC)                  99205.810
##   Bayesian (BIC)                99796.505
##   Sample-size adjusted Bayesian (BIC)  99405.877
##
## Root Mean Square Error of Approximation:
##
##   RMSEA                           0.060
##   90 Percent confidence interval - lower   0.058
##   90 Percent confidence interval - upper   0.063
##   P-value RMSEA <= 0.05            0.000
##
## Standardized Root Mean Square Residual:
##
```

```
##   SRMR                                0.128
##
## Parameter Estimates:
##
##   Standard errors                          Standard
##   Information                              Expected
##   Information saturated (h1) model       Structured
##
## Latent Variables:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##   BioVal_cfa =~
##     BioV1             1.080    0.040   27.067    0.000    1.080    0.783
##     BioV2             1.104    0.037   29.945    0.000    1.104    0.838
##     BioV3             0.880    0.033   26.728    0.000    0.880    0.777
##     BioV4             1.166    0.043   27.226    0.000    1.166    0.787
##   AltVal_cfa =~
##     AltV1             0.728    0.040   18.127    0.000    0.728    0.603
##     AltV2             1.026    0.043   23.725    0.000    1.026    0.741
##     AltV3             0.724    0.036   20.253    0.000    0.724    0.657
##     AltV4             0.700    0.044   15.949    0.000    0.700    0.538
##     AltV5             0.895    0.037   24.437    0.000    0.895    0.758
##   EgoVal_cfa =~
##     EgoV1             1.400    0.059   23.610    0.000    1.400    0.811
##     EgoV2             1.359    0.056   24.102    0.000    1.359    0.829
##     EgoV3             0.971    0.061   15.934    0.000    0.971    0.542
##   MutualWVO_cfa =~
##     SAB1              0.640    0.036   17.767    0.000    0.913    0.605
##     SAB2              0.729    0.035   20.991    0.000    1.040    0.707
##     SAB3              0.916    0.042   21.593    0.000    1.307    0.726
##     SAB4              0.862    0.035   24.855    0.000    1.230    0.828
##     CaB1              0.930    0.040   23.194    0.000    1.328    0.776
##     CaB2              0.801    0.042   19.274    0.000    1.144    0.653
##     CaB3              0.639    0.032   20.143    0.000    0.912    0.683
##     CaB4              0.797    0.036   22.204    0.000    1.137    0.746
##     CaB5              0.565    0.032   17.617    0.000    0.807    0.603
##   AwareCon_cfa =~
##     AC1               0.752    0.034   22.389    0.000    0.921    0.762
##     AC2               0.711    0.032   21.928    0.000    0.871    0.746
##     AC3               0.553    0.038   14.734    0.000    0.677    0.519
##     AC4               0.601    0.035   17.144    0.000    0.736    0.596
##   AscResp_cfa =~
##     AR1               1.078    0.044   24.422    0.000    1.369    0.827
##     AR2               0.702    0.039   17.976    0.000    0.891    0.619
##     AR3               1.014    0.044   23.075    0.000    1.288    0.780
##   PersNorm_cfa =~
##     PN1               0.986    0.038   25.842    0.000    1.550    0.893
```

```
##    PN2           0.995   0.040   25.128   0.000   1.564   0.867
##    PN3           1.008   0.039   25.708   0.000   1.584   0.888
##    PN4           0.740   0.033   22.402   0.000   1.163   0.772
##    PN5           0.758   0.035   21.507   0.000   1.191   0.742
##   Intent_cfa =~
##    Int1          0.973   0.035   27.963   0.000   1.560   0.846
##    Int2          1.058   0.033   32.243   0.000   1.695   0.949
##    Int3          1.052   0.033   32.106   0.000   1.686   0.944
##
## Regressions:
##                Estimate  Std.Err  z-value  P(>|z|)  Std.lv  Std.all
##   MutualWVO_cfa ~
##    BioVal_cfa      1.166   0.100   11.640   0.000   0.817   0.817
##    AltVal_cfa     -0.250   0.084   -2.991   0.003  -0.175  -0.175
##    EgoVal_cfa      0.116   0.045    2.558   0.011   0.081   0.081
##   AwareCon_cfa ~
##    MutualWVO_cfa   0.496   0.038   13.032   0.000   0.578   0.578
##   AscResp_cfa ~
##    AwareCon_cfa    0.639   0.049   13.168   0.000   0.617   0.617
##   PersNorm_cfa ~
##    AscResp_cfa     0.954   0.061   15.750   0.000   0.771   0.771
##   Intent_cfa ~
##    PersNorm_cfa    0.797   0.045   17.881   0.000   0.782   0.782
##
## Covariances:
##                Estimate  Std.Err  z-value  P(>|z|)  Std.lv  Std.all
##  .PN4 ~~
##   .PN5           0.571   0.044   12.905   0.000   0.571   0.553
##  .CaB3 ~~
##   .CaB5          0.525   0.043   12.211   0.000   0.525   0.504
##   .CaB4          0.426   0.042   10.234   0.000   0.426   0.430
##  .CaB4 ~~
##   .CaB5          0.422   0.044    9.608   0.000   0.422   0.389
##  .AltV1 ~~
##   .AltV3         0.320   0.035    9.198   0.000   0.320   0.401
##   BioVal_cfa ~~
##    AltVal_cfa      0.746   0.022   33.700   0.000   0.746   0.746
##    EgoVal_cfa      0.164   0.038    4.268   0.000   0.164   0.164
##   AltVal_cfa ~~
##    EgoVal_cfa      0.152   0.041    3.742   0.000   0.152   0.152
##
## Intercepts:
##                Estimate  Std.Err  z-value  P(>|z|)  Std.lv  Std.all
##   .BioV1         5.497   0.046  119.666   0.000   5.497   3.989
##   .BioV2         5.586   0.044  127.259   0.000   5.586   4.242
##   .BioV3         5.954   0.038  157.677   0.000   5.954   5.256
```

```
##    .BioV4          5.119    0.049  103.632    0.000    5.119    3.454
##    .AltV1          5.926    0.040  147.345    0.000    5.926    4.911
##    .AltV2          5.171    0.046  111.969    0.000    5.171    3.732
##    .AltV3          6.093    0.037  166.093    0.000    6.093    5.536
##    .AltV4          5.852    0.043  134.947    0.000    5.852    4.498
##    .AltV5          5.737    0.039  145.648    0.000    5.737    4.855
##    .EgoV1          2.621    0.058   45.570    0.000    2.621    1.519
##    .EgoV2          2.511    0.055   45.952    0.000    2.511    1.532
##    .EgoV3          3.949    0.060   66.091    0.000    3.949    2.203
##    .SAB1           5.200    0.050  103.314    0.000    5.200    3.444
##    .SAB2           5.147    0.049  104.985    0.000    5.147    3.499
##    .SAB3           4.452    0.060   74.192    0.000    4.452    2.473
##    .SAB4           5.039    0.050  101.772    0.000    5.039    3.392
##    .CaB1           5.062    0.057   88.797    0.000    5.062    2.960
##    .CaB2           4.231    0.058   72.485    0.000    4.231    2.416
##    .CaB3           5.596    0.045  125.712    0.000    5.596    4.190
##    .CaB4           5.257    0.051  103.542    0.000    5.257    3.451
##    .CaB5           5.712    0.045  128.027    0.000    5.712    4.268
##    .AC1            5.699    0.040  141.418    0.000    5.699    4.714
##    .AC2            5.488    0.039  141.122    0.000    5.488    4.704
##    .AC3            5.261    0.043  120.988    0.000    5.261    4.033
##    .AC4            5.209    0.041  126.530    0.000    5.209    4.218
##    .AR1            4.512    0.055   81.731    0.000    4.512    2.724
##    .AR2            5.179    0.048  107.837    0.000    5.179    3.595
##    .AR3            4.293    0.055   77.960    0.000    4.293    2.599
##    .PN1            4.306    0.058   74.451    0.000    4.306    2.482
##    .PN2            3.636    0.060   60.484    0.000    3.636    2.016
##    .PN3            3.892    0.059   65.496    0.000    3.892    2.183
##    .PN4            4.989    0.050   99.364    0.000    4.989    3.312
##    .PN5            4.953    0.054   92.514    0.000    4.953    3.084
##    .Int1           3.944    0.061   64.142    0.000    3.944    2.138
##    .Int2           3.489    0.060   58.563    0.000    3.489    1.952
##    .Int3           3.350    0.060   56.272    0.000    3.350    1.876
##     BioVal_cfa     0.000                               0.000    0.000
##     AltVal_cfa     0.000                               0.000    0.000
##     EgoVal_cfa     0.000                               0.000    0.000
##    .MutualWVO_cfa  0.000                               0.000    0.000
##    .AwareCon_cfa   0.000                               0.000    0.000
##    .AscResp_cfa    0.000                               0.000    0.000
##    .PersNorm_cfa   0.000                               0.000    0.000
##    .Intent_cfa     0.000                               0.000    0.000
##
## Variances:
##                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##    .BioV1          0.734    0.042   17.321    0.000    0.734    0.386
##    .BioV2          0.515    0.033   15.389    0.000    0.515    0.297
```

```
##    .BioV3          0.509    0.029   17.494    0.000    0.509    0.397
##    .BioV4          0.837    0.049   17.237    0.000    0.837    0.381
##    .AltV1          0.926    0.050   18.457    0.000    0.926    0.636
##    .AltV2          0.866    0.055   15.731    0.000    0.866    0.451
##    .AltV3          0.688    0.039   17.675    0.000    0.688    0.568
##    .AltV4          1.203    0.062   19.423    0.000    1.203    0.711
##    .AltV5          0.595    0.039   15.132    0.000    0.595    0.426
##    .EgoV1          1.018    0.112    9.123    0.000    1.018    0.342
##    .EgoV2          0.840    0.103    8.167    0.000    0.840    0.313
##    .EgoV3          2.270    0.118   19.204    0.000    2.270    0.706
##    .SAB1           1.446    0.072   19.960    0.000    1.446    0.634
##    .SAB2           1.081    0.057   19.027    0.000    1.081    0.500
##    .SAB3           1.532    0.082   18.774    0.000    1.532    0.473
##    .SAB4           0.693    0.042   16.419    0.000    0.693    0.314
##    .CaB1           1.163    0.065   17.890    0.000    1.163    0.398
##    .CaB2           1.759    0.090   19.594    0.000    1.759    0.574
##    .CaB3           0.952    0.050   19.171    0.000    0.952    0.534
##    .CaB4           1.028    0.056   18.382    0.000    1.028    0.443
##    .CaB5           1.141    0.058   19.837    0.000    1.141    0.637
##    .AC1            0.613    0.043   14.361    0.000    0.613    0.419
##    .AC2            0.603    0.040   14.970    0.000    0.603    0.443
##    .AC3            1.243    0.064   19.436    0.000    1.243    0.730
##    .AC4            0.984    0.053   18.540    0.000    0.984    0.645
##    .AR1            0.869    0.066   13.191    0.000    0.869    0.317
##    .AR2            1.281    0.068   18.973    0.000    1.281    0.617
##    .AR3            1.071    0.070   15.407    0.000    1.071    0.392
##    .PN1            0.608    0.040   15.369    0.000    0.608    0.202
##    .PN2            0.806    0.048   16.737    0.000    0.806    0.248
##    .PN3            0.670    0.043   15.677    0.000    0.670    0.211
##    .PN4            0.916    0.048   19.027    0.000    0.916    0.404
##    .PN5            1.161    0.060   19.376    0.000    1.161    0.450
##    .Int1           0.970    0.052   18.565    0.000    0.970    0.285
##    .Int2           0.320    0.030   10.642    0.000    0.320    0.100
##    .Int3           0.346    0.031   11.340    0.000    0.346    0.109
##     BioVal_cfa     1.000                               1.000    1.000
##     AltVal_cfa     1.000                               1.000    1.000
##     EgoVal_cfa     1.000                               1.000    1.000
##    .MutualWVO_cfa  1.000                               0.491    0.491
##    .AwareCon_cfa   1.000                               0.666    0.666
##    .AscResp_cfa    1.000                               0.620    0.620
##    .PersNorm_cfa   1.000                               0.405    0.405
##    .Intent_cfa     1.000                               0.389    0.389
##
## R-Square:
##                  Estimate
##     BioV1           0.614
```

```
##    BioV2          0.703
##    BioV3          0.603
##    BioV4          0.619
##    AltV1          0.364
##    AltV2          0.549
##    AltV3          0.432
##    AltV4          0.289
##    AltV5          0.574
##    EgoV1          0.658
##    EgoV2          0.687
##    EgoV3          0.294
##    SAB1           0.366
##    SAB2           0.500
##    SAB3           0.527
##    SAB4           0.686
##    CaB1           0.602
##    CaB2           0.426
##    CaB3           0.466
##    CaB4           0.557
##    CaB5           0.363
##    AC1            0.581
##    AC2            0.557
##    AC3            0.270
##    AC4            0.355
##    AR1            0.683
##    AR2            0.383
##    AR3            0.608
##    PN1            0.798
##    PN2            0.752
##    PN3            0.789
##    PN4            0.596
##    PN5            0.550
##    Int1           0.715
##    Int2           0.900
##    Int3           0.891
##    MutualWVO_cfa    0.509
##    AwareCon_cfa     0.334
##    AscResp_cfa      0.380
##    PersNorm_cfa     0.595
##    Intent_cfa       0.611
```

APPENDIX H: VBN SEM WITH WILDLFIE VALUE ORIENTATIONS - INDIA

```
## lavaan 0.6-11 ended normally after 58 iterations
##
##   Estimator                                         ML
##   Optimization method                           NLMINB
##   Number of model parameters                       114
##
##   Number of observations                           920
##
## Model Test User Model:
##
##   Test statistic                              1415.618
##   Degrees of freedom                               515
##   P-value (Chi-square)                           0.000
##
## Model Test Baseline Model:
##
##   Test statistic                             13144.138
##   Degrees of freedom                               561
##   P-value                                        0.000
##
## User Model versus Baseline Model:
##
##   Comparative Fit Index (CFI)                    0.928
##   Tucker-Lewis Index (TLI)                       0.922
##
## Loglikelihood and Information Criteria:
##
##   Loglikelihood user model (H0)             -41737.103
##   Loglikelihood unrestricted model (H1)             NA
##
##   Akaike (AIC)                               83702.205
##   Bayesian (BIC)                             84252.184
##   Sample-size adjusted Bayesian (BIC)        83890.133
##
## Root Mean Square Error of Approximation:
##
##   RMSEA                                          0.044
##   90 Percent confidence interval - lower         0.041
##   90 Percent confidence interval - upper         0.046
##   P-value RMSEA <= 0.05                          1.000
##
## Standardized Root Mean Square Residual:
##
```

```
##   SRMR                                  0.069
##
## Parameter Estimates:
##
##   Standard errors                           Standard
##   Information                               Expected
##   Information saturated (h1) model        Structured
##
## Latent Variables:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##   BioVal_cfa =~
##     BioV1             0.546    0.028   19.344    0.000    0.546    0.619
##     BioV2             0.518    0.021   24.344    0.000    0.518    0.739
##     BioV3             0.447    0.019   23.286    0.000    0.447    0.715
##     BioV4             0.617    0.024   26.122    0.000    0.617    0.779
##   AltVal_cfa =~
##     AltV1             0.542    0.030   17.839    0.000    0.542    0.611
##     AltV3             0.597    0.039   15.207    0.000    0.597    0.532
##     AltV4             0.579    0.036   16.236    0.000    0.579    0.563
##     AltV5             0.520    0.030   17.191    0.000    0.520    0.592
##   EgoVal_cfa =~
##     EgoV1             1.605    0.199    8.068    0.000    1.605    0.882
##     EgoV2             1.230    0.157    7.811    0.000    1.230    0.669
##   MutualWVO_cfa =~
##     SAB1              0.447    0.029   15.648    0.000    0.619    0.532
##     SAB2              0.452    0.023   19.699    0.000    0.626    0.659
##     SAB3              0.529    0.029   18.417    0.000    0.732    0.619
##     SAB4              0.518    0.023   22.100    0.000    0.718    0.732
##     CaB1              0.520    0.025   20.417    0.000    0.719    0.681
##     CaB2              0.505    0.035   14.436    0.000    0.700    0.493
##     CaB3              0.514    0.026   20.025    0.000    0.712    0.673
##     CaB4              0.532    0.025   21.193    0.000    0.737    0.708
##     CaB5              0.454    0.025   18.511    0.000    0.628    0.622
##   AwareCon_cfa =~
##     AC1               0.415    0.027   15.516    0.000    0.681    0.624
##     AC2               0.426    0.026   16.311    0.000    0.699    0.667
##     AC3               0.356    0.029   12.277    0.000    0.584    0.473
##     AC4               0.395    0.026   15.111    0.000    0.648    0.604
##   AscResp_cfa =~
##     AR1               0.381    0.029   13.331    0.000    0.691    0.719
##     AR2               0.357    0.028   12.994    0.000    0.649    0.667
##     AR3               0.412    0.034   11.951    0.000    0.747    0.566
##   PersNorm_cfa =~
##     PN1               0.741    0.034   21.966    0.000    0.986    0.761
##     PN2               0.769    0.042   18.386    0.000    1.023    0.640
##     PN3               0.691    0.036   19.429    0.000    0.918    0.675
```

```
##    PN4           0.619   0.030   20.718   0.000   0.823   0.725
##    PN5           0.582   0.029   20.078   0.000   0.774   0.704
##   Intent_cfa =~
##    Int1          0.763   0.029   26.043   0.000   1.157   0.878
##    Int2          0.769   0.030   25.625   0.000   1.166   0.863
##    Int3          0.847   0.032   26.601   0.000   1.284   0.900
##
## Regressions:
##              Estimate  Std.Err  z-value  P(>|z|)  Std.lv  Std.all
##   MutualWVO_cfa ~
##    BioVal_cfa      0.582   0.109    5.336   0.000   0.420   0.420
##    AltVal_cfa      0.397   0.115    3.440   0.001   0.287   0.287
##    EgoVal_cfa      0.133   0.046    2.907   0.004   0.096   0.096
##   AwareCon_cfa ~
##    MutualWVO_cfa    0.940   0.069   13.722   0.000   0.793   0.793
##   AscResp_cfa ~
##    AwareCon_cfa    0.923   0.093    9.935   0.000   0.835   0.835
##   PersNorm_cfa ~
##    AscResp_cfa     0.483   0.046   10.578   0.000   0.659   0.659
##   Intent_cfa ~
##    PersNorm_cfa    0.858   0.055   15.485   0.000   0.752   0.752
##
## Covariances:
##              Estimate  Std.Err  z-value  P(>|z|)  Std.lv  Std.all
##  .PN4 ~~
##   .PN5           0.157   0.027    5.828   0.000   0.157   0.257
##  .CaB3 ~~
##   .CaB4          0.135   0.023    5.906   0.000   0.135   0.235
##   BioVal_cfa ~~
##    AltVal_cfa      0.806   0.026   30.946   0.000   0.806   0.806
##    EgoVal_cfa      0.108   0.041    2.629   0.009   0.108   0.108
##   AltVal_cfa ~~
##    EgoVal_cfa      0.122   0.045    2.701   0.007   0.122   0.122
##
## Intercepts:
##              Estimate  Std.Err  z-value  P(>|z|)  Std.lv  Std.all
##   .BioV1         6.482   0.029  222.897   0.000   6.482   7.349
##   .BioV2         6.583   0.023  284.938   0.000   6.583   9.394
##   .BioV3         6.655   0.021  322.812   0.000   6.655  10.643
##   .BioV4         6.462   0.026  247.565   0.000   6.462   8.162
##   .AltV1         6.362   0.029  217.755   0.000   6.362   7.179
##   .AltV3         6.108   0.037  164.955   0.000   6.108   5.438
##   .AltV4         6.292   0.034  185.649   0.000   6.292   6.121
##   .AltV5         6.247   0.029  215.531   0.000   6.247   7.106
##   .EgoV1         4.342   0.060   72.325   0.000   4.342   2.384
##   .EgoV2         4.086   0.061   67.424   0.000   4.086   2.223
```

```
##   .SAB1           6.082   0.038  158.448   0.000   6.082   5.224
##   .SAB2           6.257   0.031  199.859   0.000   6.257   6.589
##   .SAB3           5.983   0.039  153.499   0.000   5.983   5.061
##   .SAB4           6.270   0.032  194.092   0.000   6.270   6.399
##   .CaB1           6.136   0.035  176.233   0.000   6.136   5.810
##   .CaB2           5.315   0.047  113.550   0.000   5.315   3.744
##   .CaB3           6.000   0.035  171.997   0.000   6.000   5.671
##   .CaB4           6.104   0.034  177.773   0.000   6.104   5.861
##   .CaB5           6.000   0.033  180.234   0.000   6.000   5.942
##   .AC1            6.180   0.036  171.905   0.000   6.180   5.668
##   .AC2            5.971   0.035  172.824   0.000   5.971   5.698
##   .AC3            5.808   0.041  142.445   0.000   5.808   4.696
##   .AC4            5.633   0.035  159.027   0.000   5.633   5.243
##   .AR1            6.177   0.032  194.912   0.000   6.177   6.426
##   .AR2            6.162   0.032  192.101   0.000   6.162   6.333
##   .AR3            5.571   0.044  127.909   0.000   5.571   4.217
##   .PN1            5.564   0.043  130.350   0.000   5.564   4.298
##   .PN2            5.166   0.053   98.015   0.000   5.166   3.231
##   .PN3            5.376   0.045  119.822   0.000   5.376   3.950
##   .PN4            5.878   0.037  157.010   0.000   5.878   5.176
##   .PN5            6.014   0.036  166.012   0.000   6.014   5.473
##   .Int1           5.518   0.043  126.937   0.000   5.518   4.185
##   .Int2           5.407   0.045  121.282   0.000   5.407   3.999
##   .Int3           5.382   0.047  114.397   0.000   5.382   3.772
##    BioVal_cfa     0.000                           0.000   0.000
##    AltVal_cfa     0.000                           0.000   0.000
##    EgoVal_cfa     0.000                           0.000   0.000
##   .MutualWVO_cfa  0.000                           0.000   0.000
##   .AwareCon_cfa   0.000                           0.000   0.000
##   .AscResp_cfa    0.000                           0.000   0.000
##   .PersNorm_cfa   0.000                           0.000   0.000
##   .Intent_cfa     0.000                           0.000   0.000
##
## Variances:
##                 Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##   .BioV1          0.480   0.025   19.046   0.000   0.480   0.617
##   .BioV2          0.223   0.013   16.711   0.000   0.223   0.453
##   .BioV3          0.191   0.011   17.351   0.000   0.191   0.489
##   .BioV4          0.247   0.016   15.377   0.000   0.247   0.394
##   .AltV1          0.492   0.028   17.468   0.000   0.492   0.626
##   .AltV3          0.905   0.048   18.870   0.000   0.905   0.717
##   .AltV4          0.722   0.039   18.390   0.000   0.722   0.683
##   .AltV5          0.502   0.028   17.871   0.000   0.502   0.650
##   .EgoV1          0.739   0.622    1.188   0.235   0.739   0.223
##   .EgoV2          1.865   0.375    4.977   0.000   1.865   0.552
##   .SAB1           0.972   0.048   20.370   0.000   0.972   0.717
```

```
##   .SAB2           0.510   0.026   19.341   0.000   0.510   0.565
##   .SAB3           0.861   0.044   19.742   0.000   0.861   0.616
##   .SAB4           0.445   0.024   18.266   0.000   0.445   0.464
##   .CaB1           0.598   0.031   19.071   0.000   0.598   0.536
##   .CaB2           1.526   0.074   20.572   0.000   1.526   0.757
##   .CaB3           0.613   0.032   18.976   0.000   0.613   0.548
##   .CaB4           0.542   0.029   18.517   0.000   0.542   0.499
##   .CaB5           0.625   0.032   19.716   0.000   0.625   0.613
##   .AC1            0.726   0.039   18.413   0.000   0.726   0.611
##   .AC2            0.610   0.035   17.618   0.000   0.610   0.555
##   .AC3            1.188   0.059   20.095   0.000   1.188   0.777
##   .AC4            0.734   0.039   18.728   0.000   0.734   0.636
##   .AR1            0.447   0.029   15.643   0.000   0.447   0.484
##   .AR2            0.526   0.031   17.132   0.000   0.526   0.556
##   .AR3            1.187   0.063   18.943   0.000   1.187   0.680
##   .PN1            0.704   0.043   16.495   0.000   0.704   0.420
##   .PN2            1.510   0.079   18.995   0.000   1.510   0.591
##   .PN3            1.009   0.055   18.477   0.000   1.009   0.545
##   .PN4            0.612   0.036   17.100   0.000   0.612   0.474
##   .PN5            0.609   0.035   17.505   0.000   0.609   0.504
##   .Int1           0.400   0.027   14.612   0.000   0.400   0.230
##   .Int2           0.468   0.030   15.577   0.000   0.468   0.256
##   .Int3           0.387   0.030   12.805   0.000   0.387   0.190
##    BioVal_cfa     1.000                              1.000   1.000
##    AltVal_cfa     1.000                              1.000   1.000
##    EgoVal_cfa     1.000                              1.000   1.000
##   .MutualWVO_cfa  1.000                              0.522   0.522
##   .AwareCon_cfa   1.000                              0.371   0.371
##   .AscResp_cfa    1.000                              0.304   0.304
##   .PersNorm_cfa   1.000                              0.566   0.566
##   .Intent_cfa     1.000                              0.435   0.435
##
## R-Square:
##                   Estimate
##    BioV1           0.383
##    BioV2           0.547
##    BioV3           0.511
##    BioV4           0.606
##    AltV1           0.374
##    AltV3           0.283
##    AltV4           0.317
##    AltV5           0.350
##    EgoV1           0.777
##    EgoV2           0.448
##    SAB1            0.283
##    SAB2            0.435
```

```
##    SAB3           0.384
##    SAB4           0.536
##    CaB1           0.464
##    CaB2           0.243
##    CaB3           0.452
##    CaB4           0.501
##    CaB5           0.387
##    AC1            0.389
##    AC2            0.445
##    AC3            0.223
##    AC4            0.364
##    AR1            0.516
##    AR2            0.444
##    AR3            0.320
##    PN1            0.580
##    PN2            0.409
##    PN3            0.455
##    PN4            0.526
##    PN5            0.496
##    Int1           0.770
##    Int2           0.744
##    Int3           0.810
##    MutualWVO_cfa    0.478
##    AwareCon_cfa     0.629
##    AscResp_cfa      0.696
##    PersNorm_cfa     0.434
##    Intent_cfa       0.565
```

APPENDIX I: SURVEY INSTRUMENT

Informed Consent

"Researchers at Michigan State University are studying wildlife crime. Results of this survey will help researchers better understand how people think and feel about this issue. Your participation is completely anonymous and voluntary. Your responses are not tied to any personally identifying information. You can withdraw from the survey at any time or refuse to answer any question without penalty. Only the researchers associated with this study will have access to the survey data. The survey data will be maintained on a secure electronic device and only the lead researcher will have access to that device.
By completing this questionnaire, you are acknowledging that any data collected in this study can be used in research, and for related publications and presentations.
We estimate that this survey should take no longer than 20 minutes to complete. You must be 18 years of age or older to participate in this study.
For further information about this study, please contact Apoorva Joshi at joshiap1@msu.edu or MSU's IRB at irb@msu.edu

- *Are you 18 years of age or older?* (Yes/No)
- *Do you consent to participate in this survey?* (Yes/No)

Introduction

The term 'wildlife crime' includes illegal acts such as poaching (illegal hunting of wildlife), as well as the trafficking, smuggling, and illegal trade in wild plants and animals – both living and dead. This illegal trade in exotic live animals and wildlife parts and products occurs across international and local borders. Globally, wildlife crime is regarded as one of the largest organized criminal operations behind the trafficking of drugs, weapons, and humans.
In the following sections, please pay close attention to each question and respond as honestly as possible.

Questionnaire

Order will be randomized within each question block – i.e. each construct's set of items.
In the following section, you will be asked about your thoughts about the natural environment. Please answer all questions in this survey as honestly as you can.
For each of the following questions, please select from the options below that most closely resembles your honest answer.

New Ecological Paradigm

Please indicate the extent to which you agree with each statement below:
1 = *Strongly disagree*; 2 = *Disagree*; 3 = *Somewhat disagree*; 4 = *Neither agree nor disagree*; 5 = *Somewhat agree*; 6 = *Agree*; 7 = *Strongly agree*

- ***Nep1:*** "We are approaching the limit of the number of people the earth can support."
- ***Nep2:*** "Humans have the right to modify the natural environment to suit their needs."

- ***Nep3:*** "When humans interfere with nature, it often produces disastrous consequences."
- ***Nep4:*** "Human ingenuity will ensure that we do not make the earth unlivable."
- ***Nep5:*** "Humans are severely abusing the environment."
- ***Nep6:*** "The earth has plenty of natural resources if we just learn how to develop them."
- ***Nep7:*** "Plants and animals have as much right as humans to exist."
- ***Nep8:*** "The balance of nature is strong enough to cope with the impacts of modern industrial nations."
- ***Nep9:*** "Despite our special abilities, humans are still subject to the laws of nature."
- ***Nep10:*** "The so-called 'ecological crisis' facing humankind has been greatly exaggerated."
- ***Nep11:*** "The earth is like a spaceship with very limited room and resources."
- ***Nep12:*** "Humans were meant to rule over the rest of nature."
- ***Nep13:*** "The balance of nature is very delicate and easily upset."
- ***Nep14:*** "Humans will eventually learn enough about how nature works to be able to control it."
- ***Nep15:*** "If things continue on their present course, we will soon experience a major ecological catastrophe."

In the following section, you will be asked about your thoughts on the relationship between people and wildlife.

Wildlife Value Orientations
Please indicate the extent to which you agree or disagree with each statement below:
1 = *Strongly disagree*; 2 = *Disagree*; 3 = *Somewhat disagree*; 4 = *Neither agree nor disagree*; 5 = *Somewhat agree*; 6 = *Agree*; 7 = *Strongly agree*

- ***AUB1:*** "Humans should manage fish and wildlife populations so that humans benefit."
- ***AUB2:*** "The needs of humans should take priority over fish and wildlife protection."
- ***AUB3:*** "It is acceptable for people to kill wildlife if they think it poses a threat to their life."
- ***AUB4:*** "It is acceptable for people to kill wildlife if they think it poses a threat to their property."
- ***AUB5:*** "Fish and wildlife are on earth primarily for people to use."
- ***HuB1:*** "We should strive for a world where there's an abundance of fish and wildlife for hunting and fishing."
- ***HuB2:*** "Hunting is cruel and inhumane to the animals." (R)
- ***HuB3:*** "Hunting does not respect the lives of animals." (R)
- ***HuB4:*** "People who want to hunt should be provided the opportunity to do so."
- ***SAB1:*** "We should strive for a world where humans and fish and wildlife can live side by side without fear."
- ***SAB2:*** "I view all living things as part of one big family."
- ***SAB3:*** "Animals should have rights similar to the rights of humans."

- ***SAB4:*** “Wildlife are like my family and I want to protect them.”
- ***CaB1:*** “I care about animals as much as I do other people.”
- ***CaB2:*** “It would be more rewarding to me to help animals rather than people.”
- ***CaB3:*** “I take great comfort in the relationships I have with animals.”
- ***CaB4:*** “I feel a strong emotional bond with animals.”
- ***CaB5:*** “I value the sense of companionship I receive from animals.”

The following sections include questions about the problems associated with wildlife crime and who you think is responsible for dealing with them.

Awareness of Consequences
Please indicate the extent to which you agree with each statement below:
1 = *Strongly disagree*; 2 = *Disagree*; 3 = *Somewhat disagree*; 4 = *Neither agree nor disagree*; 5 = *Somewhat agree*; 6 = *Agree*; 7 = *Strongly agree*

- ***AC1:*** “Wildlife crimes cause biodiversity loss, exhaustion of natural resources, and species extinction.”
- ***AC2:*** “Wildlife crimes generate environmental impacts on the neighboring areas and wider environment.”
- ***AC3:*** “Wildlife crimes such as illegal international trade in exotic species can cause the spread of deadly zoonotic pathogens and viruses.”
- ***AC4:*** ““Conservation organizations help to curb wildlife crime and mitigate its impacts.”

Ascription of Responsibility
Please indicate the extent to which you agree with each statement below:
1 = *Strongly disagree*; 2 = *Disagree*; 3 = *Somewhat disagree*; 4 = *Neither agree nor disagree*; 5 = *Somewhat agree*; 6 = *Agree*; 7 = *Strongly agree*

- ***AR1:*** “Every citizen must take responsibility for mitigating the environmental, economic, and health issues linked to wildlife crimes by donating money to conservation organizations.”
- ***AR2:*** “The authorities are responsible for mitigating the environmental, economic, and health issues linked to wildlife crimes by financially supporting conservation organizations.”
- ***AR3:*** “I am responsible for mitigating the environmental, economic, and health issues linked to wildlife crimes by donating money to conservation organizations.”

In the following few sections, you will be asked about your thoughts on donating money to conservation organizations to help reduce wildlife crime. Please read questions carefully.

Attitude
For each of the following questions, please select the option that most closely resembles your honest answer.
1 = *Strongly disagree*; 2 = *Disagree*; 3 = *Somewhat disagree*; 4 = *Neither agree nor disagree*; 5 = *Somewhat agree*; 6 = *Agree*; 7 = *Strongly agree*

- "I think the idea of donating money to conservation organizations to help reduce wildlife crime is ________."
    - ***Att1***: Very positive
    - ***Att2***: Very responsible
    - ***Att3***: Very intelligent
    - ***Att4***: Very useful
    - ***Att5***: Very ecologically helpful

Subjective Norms
Please indicate the extent to which you agree with each statement below:
1 = *Strongly disagree*; 2 = *Disagree*; 3 = *Somewhat disagree*; 4 = *Neither agree nor disagree*; 5 = *Somewhat agree*; 6 = *Agree*; 7 = *Strongly agree*

- ***SN1***: "Most people who are important to me think that one should donate money to conservation organizations to help reduce wildlife crime."
- ***SN2***: "Most people who are important to me expect that I will donate money to conservation organizations to help reduce wildlife crime."
- ***SN3***: "Those people whose opinions I value would donate money to conservation organizations to help reduce wildlife crime."

Personal Norms
Please indicate the extent to which you agree with each statement below:
1 = *Strongly disagree*; 2 = *Disagree*; 3 = *Somewhat disagree*; 4 = *Neither agree nor disagree*; 5 = *Somewhat agree*; 6 = *Agree*; 7 = *Strongly agree*

- ***PN1:*** "I feel I ought to donate money to conservation organizations to help reduce wildlife crime."
- ***PN2:*** "I would feel guilty if I did not donate money to conservation organizations to help reduce wildlife crime."
- ***PN3:*** "I feel morally obligated to donate money to conservation organizations to help reduce wildlife crime regardless of what others are doing."
- ***PN4:*** "I feel that donating money to conservation organizations to help reduce wildlife crime is the right thing to do."
- ***PN5:*** "I would feel good about myself if I donated money to conservation organizations to help reduce wildlife crime."

Perceived Behavioral Control
Please indicate the extent to which you agree with each statement below:
1 = *Strongly disagree*; 2 = *Disagree*; 3 = *Somewhat disagree*; 4 = *Neither agree nor disagree*; 5 = *Somewhat agree*; 6 = *Agree*; 7 = *Strongly agree*

- ***PBC1:*** "I am confident that if I want, I can donate money to conservation organizations to help reduce wildlife crime."
- ***PBC2:*** "I have sufficient resources to donate money to conservation organizations to help reduce wildlife crime."
- ***PBC3:*** "I have enough time to donate money to conservation organizations to help reduce wildlife crime."

- ***PBC4:*** "I have enough opportunities to donate money to conservation organizations to help reduce wildlife crime."
- ***PBC5***: "Donating money to conservation organizations to help reduce wildlife crime is completely up to me."
- ***PBC6:*** "If I donated money to conservation organizations, it would help them to reduce wildlife crime."

Intention
Please indicate the extent to which you agree with each statement below:
1 = *Strongly disagree*; 2 = *Disagree*; 3 = *Somewhat disagree*; 4 = *Neither agree nor disagree*; 5 = *Somewhat agree*; 6 = *Agree*; 7 = *Strongly agree*

- ***Int1:*** "I am willing to donate money to conservation organizations within the next month to help reduce wildlife crime."
- ***Int2:*** "I plan to donate money to conservation organizations within the next month to help reduce wildlife crime."
- ***Int3:*** "I will definitely donate money to conservation organizations within the next month to help reduce wildlife crime."

In the following section, you will be asked about what you consider generally important in your life.

Values
<u>How important are each of the following to you as guiding principles in your life?</u>
1 = *Not at all important*; 2 = *Low importance*; 3 = *Slightly important*; 4 = *Neutral*; 5 = *Moderately important*; 6 = *Very important*; 7 = *Extremely important*

- How important is it to you ________?
    - ***Bio1:*** To prevent environmental pollution.
    - ***Bio2:*** To protect the environment.
    - ***Bio3:*** To respect nature.
    - ***Bio4:*** To be in unity with nature.
- How important is it to you ________?
    - ***Alt1:*** That every person has equal opportunities.
    - ***Alt2:*** To take care of those who are worse off.
    - ***Alt3:*** That every person is treated justly.
    - ***Alt4:*** That there is no war or conflict.
    - ***Alt5:*** To be helpful to others.
- How important is it to you ________?
    - ***Ego1:*** To have control over others' actions.
    - ***Ego2:*** To have authority over others.
    - ***Ego3:*** To be influential.
    - ***Ego4:*** To have money and possessions.
    - ***Ego5:*** To work hard and be ambitious.

In this final section, you will be asked for general information about yourself. Please remember that none of your responses in this survey can directly identify you since all responses are anonymous.

Other Questions and Demographic Module

- ***Gen:*** What gender do you identify as? Please select one of the options below:
    - Female
    - Male
    - Non-binary
    - Transgender
    - Other
    - Prefer not to answer
- ***Age:*** What is your age?
    - 18 – 29 years old
    - 30 – 45 years old
    - 46 – 60 years old
    - 61 – 75 years old
    - More than 75 years old
- ***Edu:*** What is the highest degree or level of education you have completed?
    - No formal education
    - (*For India* – SSC/ICSE/CBSE = Std. 10 equivalent)
    - High School Diploma (*For India* - HSC/Grade 12 equivalent)
    - Vocational/technical/trade school (*For India* – Professional diploma)
    - Bachelor's Degree
    - Master's Degree
    - Ph.D. or higher
    - Other (blank to include participant's response)
    - Prefer not to say
- ***Employ:*** What is your current employment status?
    - Employed Full-Time/Self-employed
    - Employed Part-Time
    - Interning
    - Unemployed – Looking for work
    - Unemployed – Not looking for work
    - Retired
    - Other
    - Prefer not to say
- ***Income***: What is your total annual income?
    - Less than $20,000 - *India:* Less than ₹2,50,000
    - $20,001 to $40,000 - *India:* ₹2,50,001 to ₹5,00,000
    - $40,001 to $60,000 - *India:* ₹5,00,001 to ₹7,50,000
    - $60,001 to $80,000 - *India:* ₹7,50,001 to ₹10,00,000
    - $80,001 to $100,000 - *India:* ₹10,00,001 to ₹12,50,000
    - $100,001 or over - *India:* ₹12,50,001 or more
- ***Polit:*** Generally speaking, how would you describe your political viewpoint?

- Very conservative
- Slightly conservative
- Neither conservative nor liberal
- Slightly liberal
- Very liberal

Conclusion

Thank you for participating in this survey. Your responses have been successfully recorded. For questions or concerns related to this study, please contact Apoorva Joshi at joshiap1@msu.edu

APPENDIX J: CROSS-NATIONAL DIFFERENCES IN RESPONSES TO ITEMS

Attitude

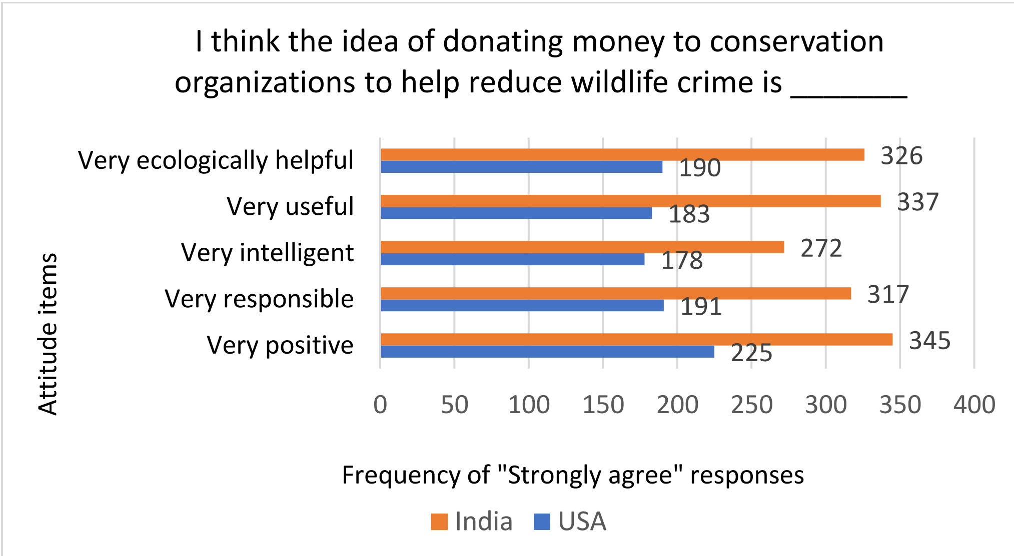

Figure 23 - Number of respondents who strongly agreed with attitude items

Subjective Norms

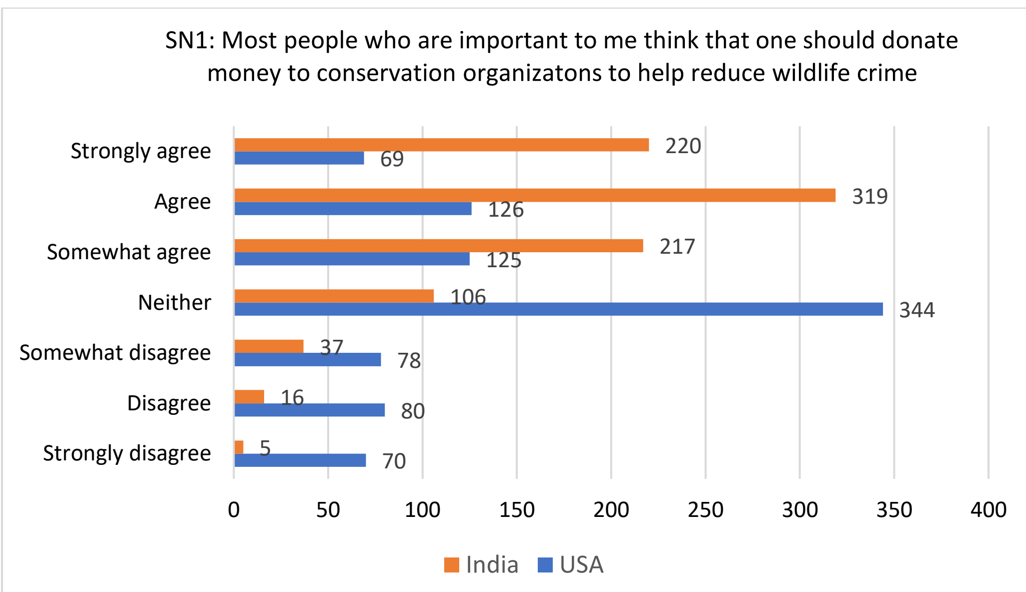

Figure 24 - Cross-national distribution of responses to item SN1

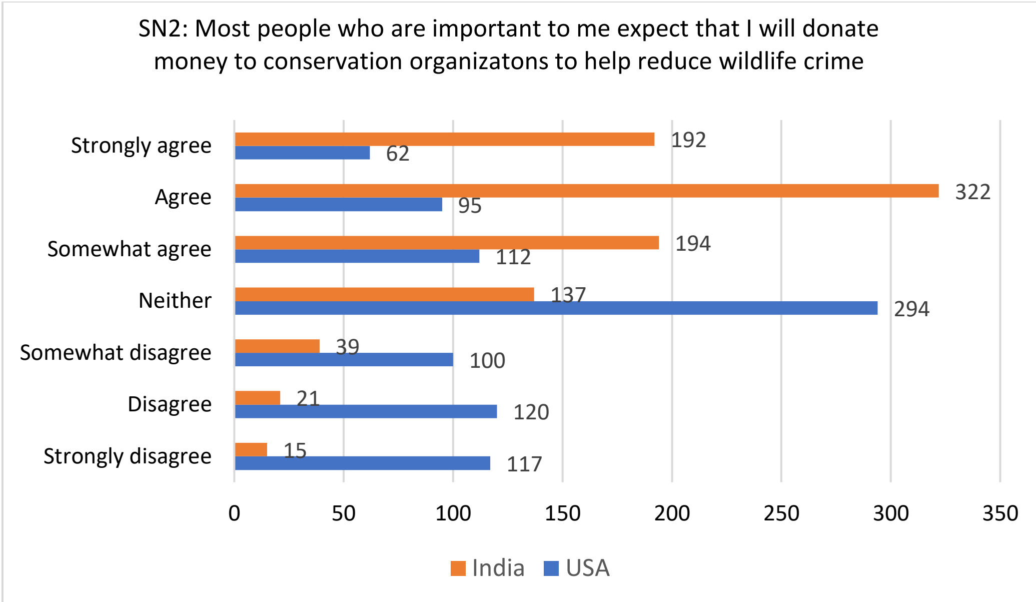

Figure 25 - Cross-national distribution of responses to item SN2

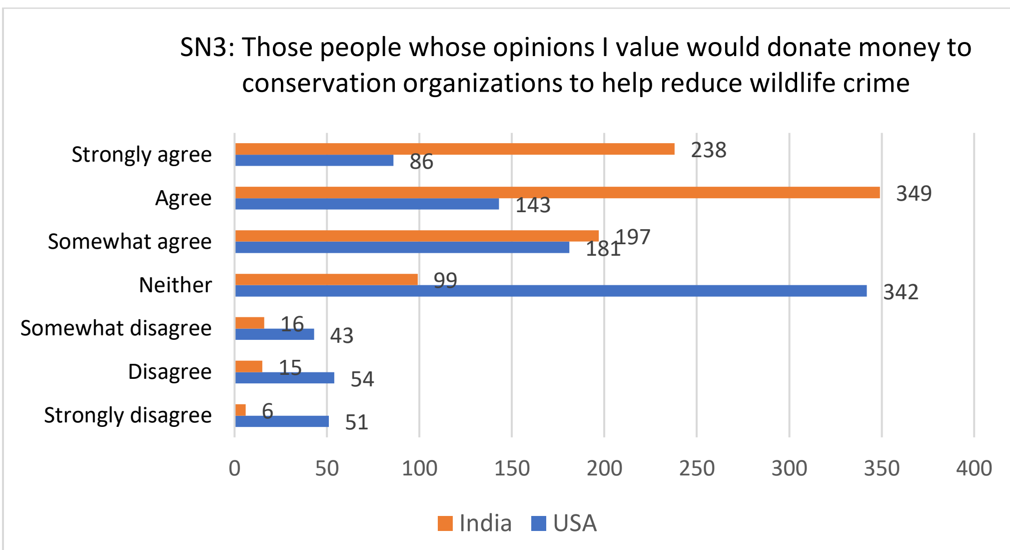

Figure 26 - Cross-national distribution of responses to item SN3

Perceived Behavioral Control

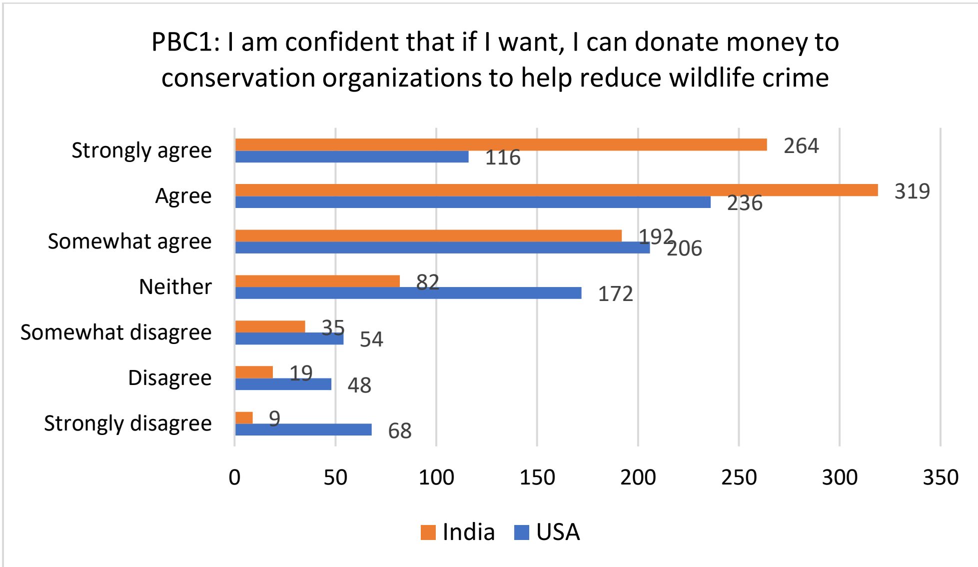

Figure 27 - Cross-national distribution of responses to item PBC1

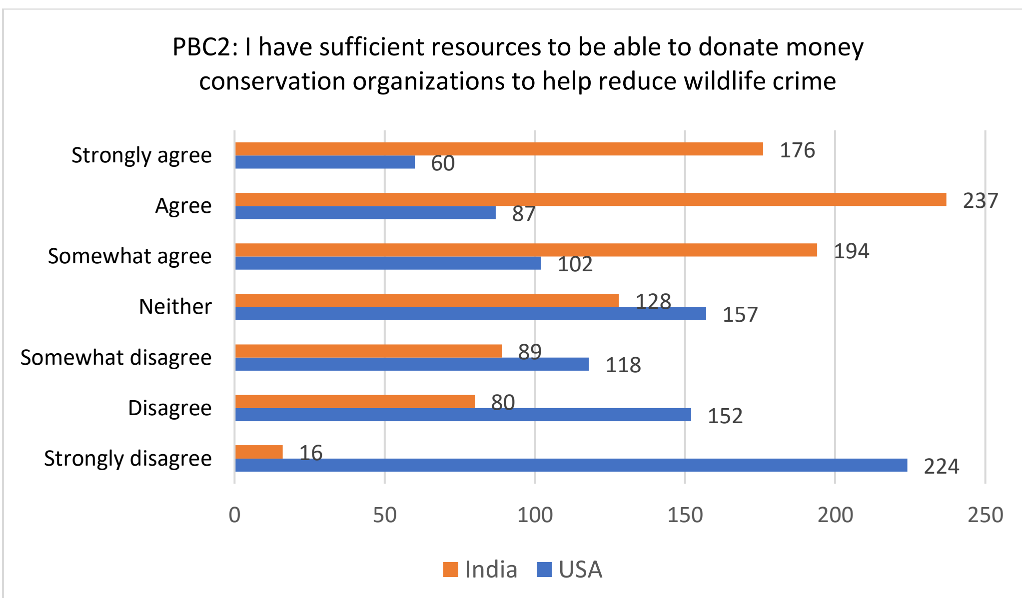

Figure 28 - Cross-national distribution of responses to item PBC2

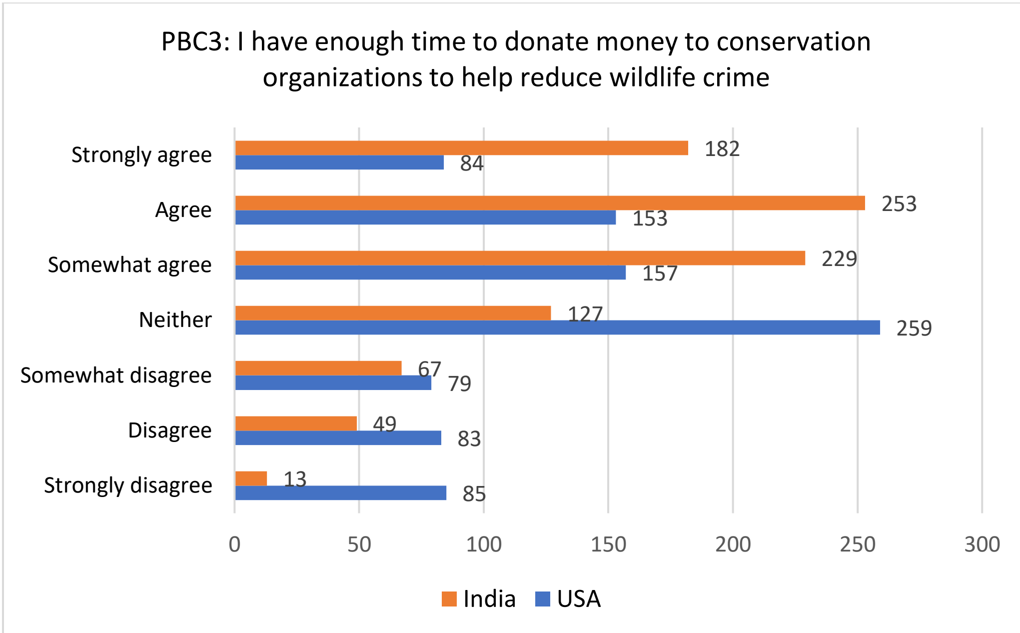

Figure 29 - Cross-national distribution of responses to item PBC3

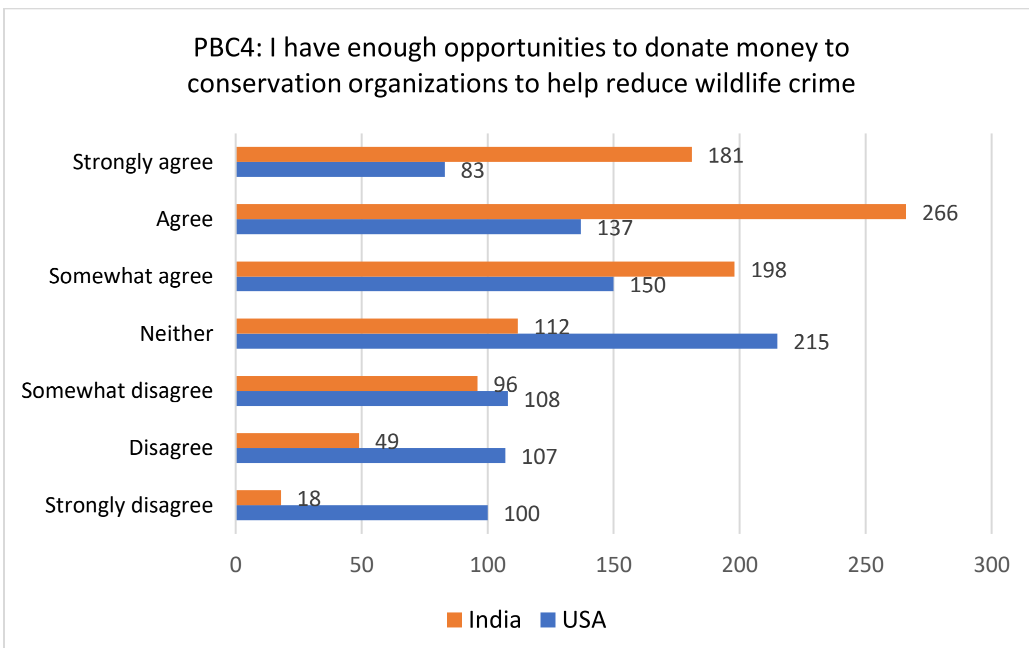

Figure 30 - Cross-national distribution of responses to item PBC4

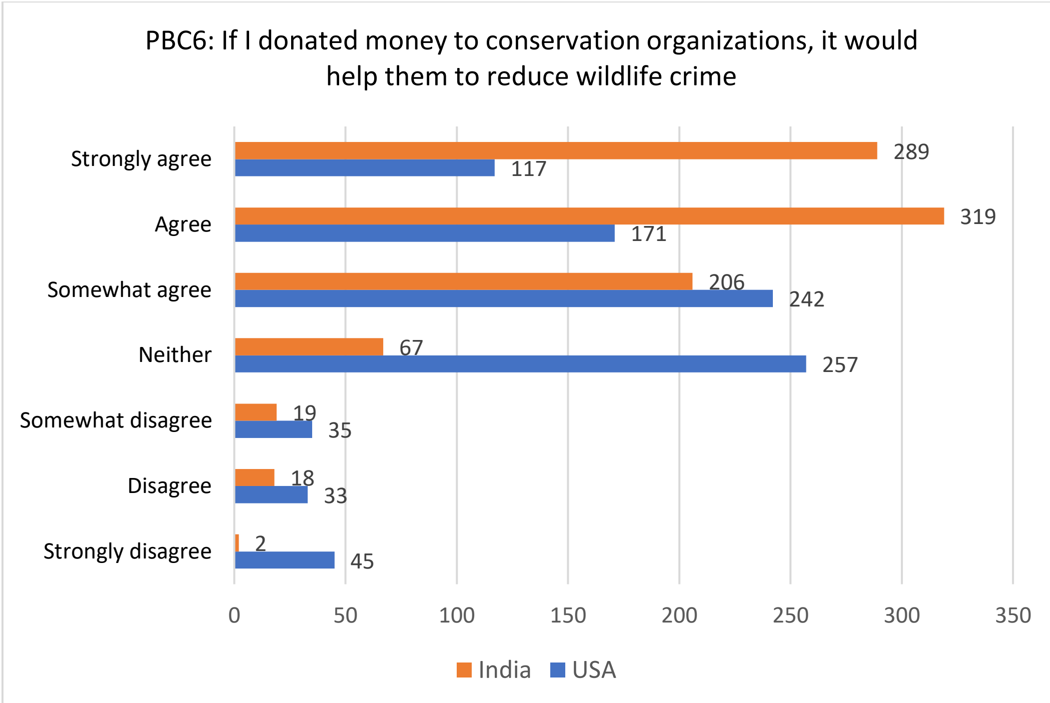

Figure 31 - Cross-national distribution of responses to item PBC6

Intentions to Donate Money to Conservation Organizations

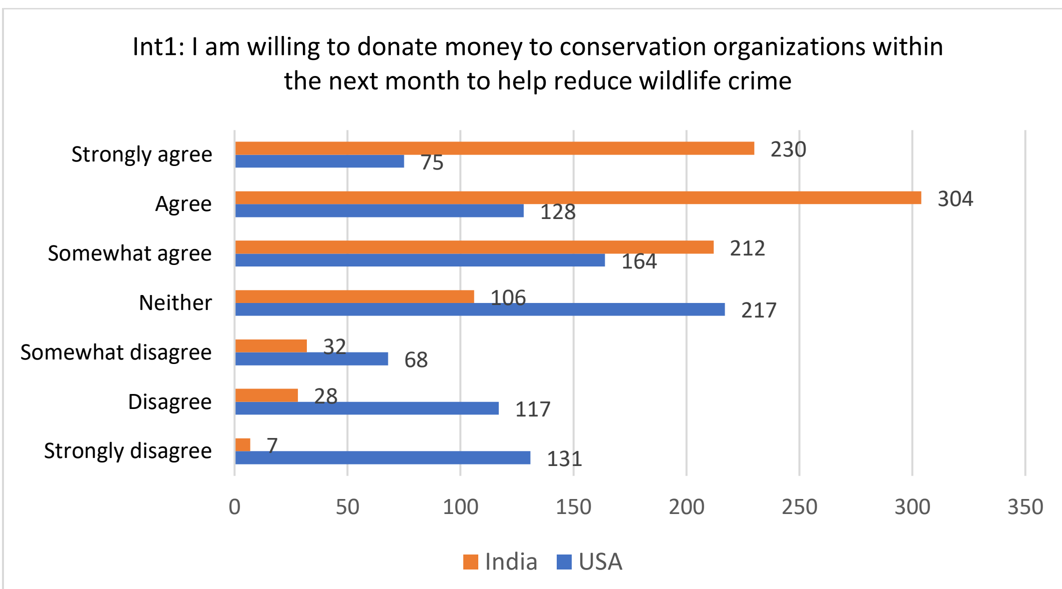

Figure 32 - Cross-national distribution of responses to item Int1

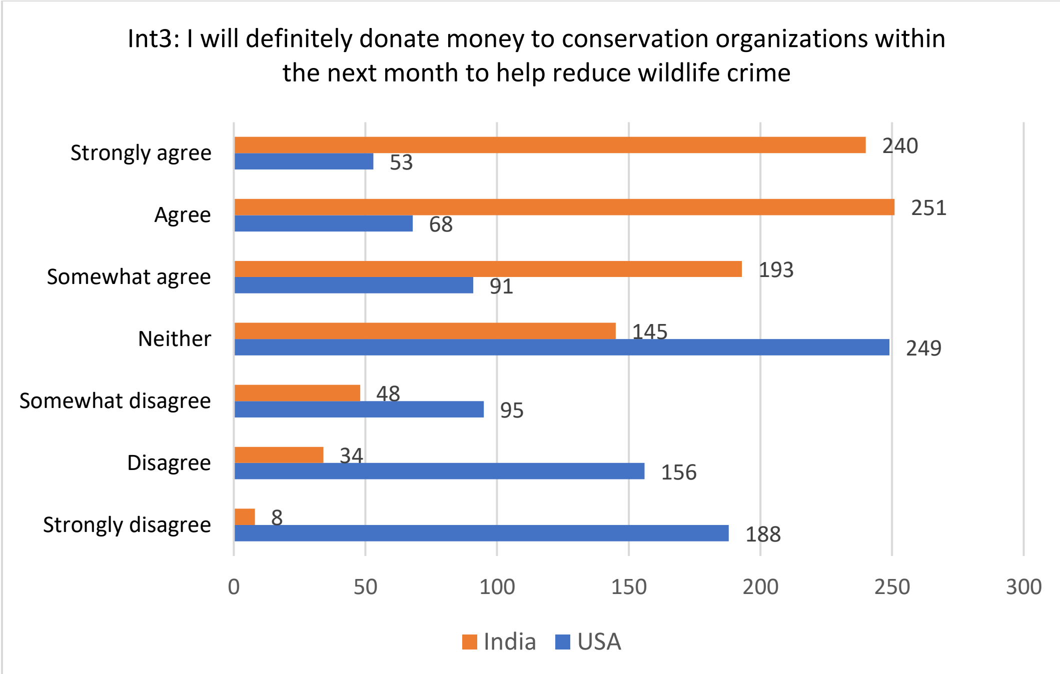

Figure 33 - Cross-national distribution of responses to item Int3

Biospheric Values

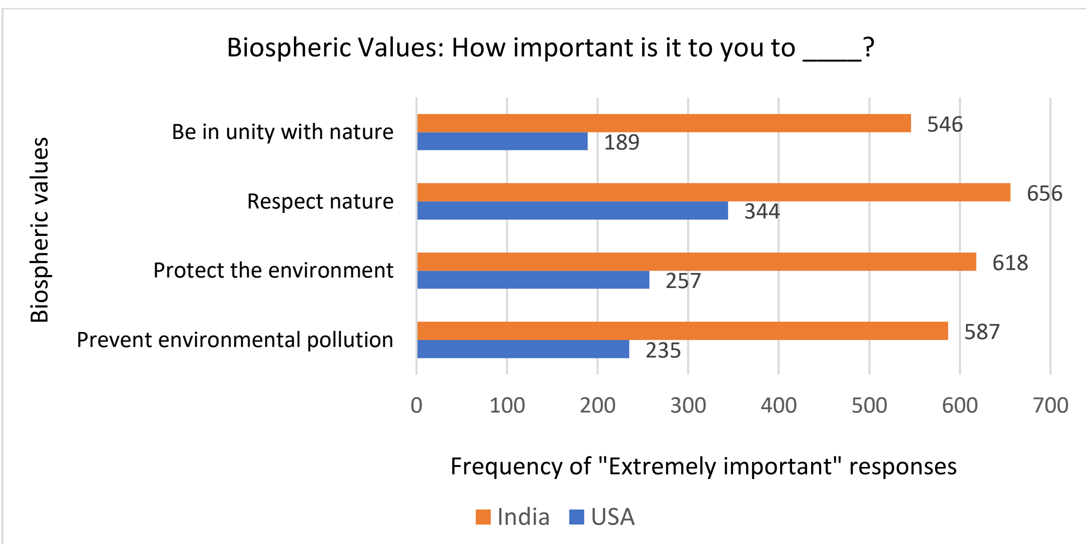

Figure 34 - Cross-national distribution of responses to biospheric value items

Altruistic Values

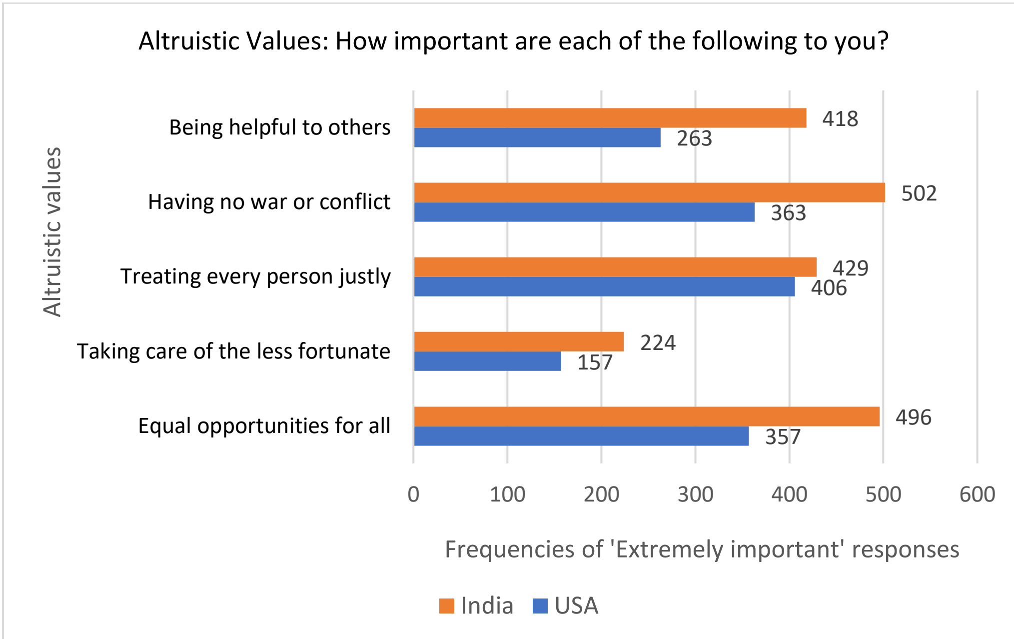

Figure 35 - Cross-national distribution of responses to altruistic value items

Egoistic Values

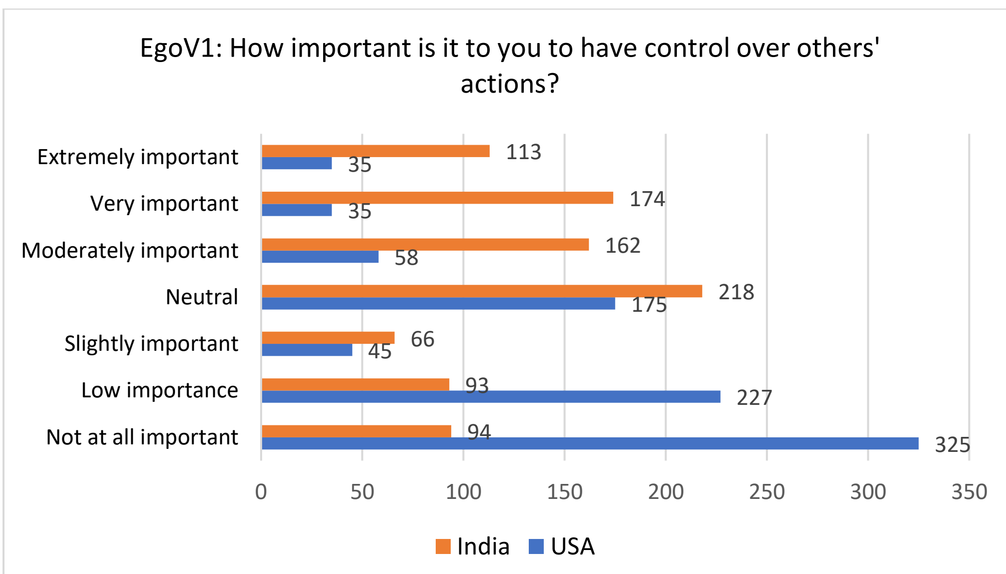

Figure 36 - Cross-national distribution of responses to item EgoV1

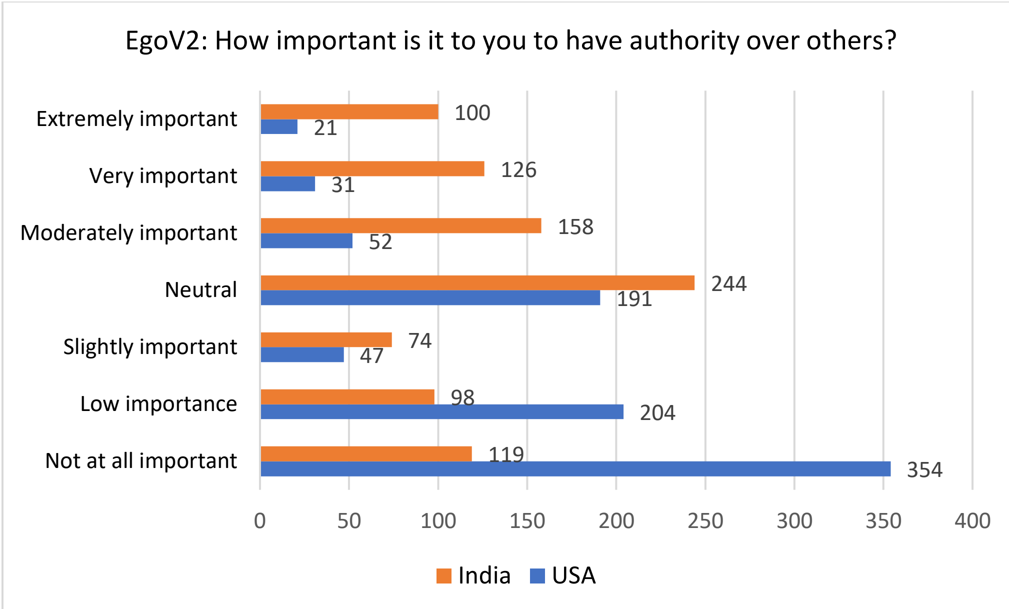

Figure 37 - Cross-national distribution of responses to item EgoV2

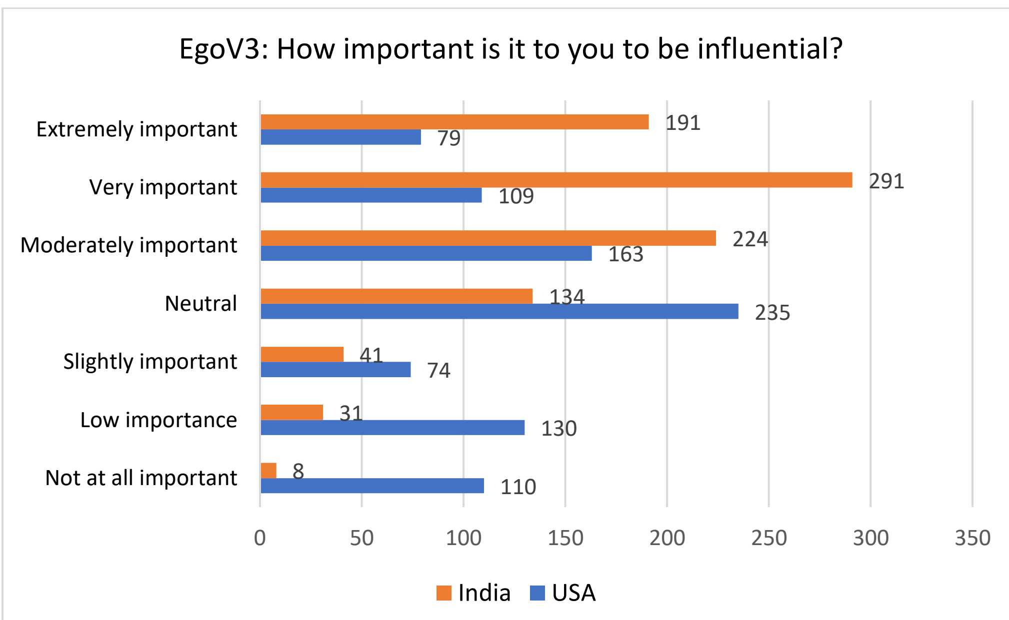

Figure 38 - Cross-national distribution of responses to item EgoV3

Mutualistic Wildlife Value Orientations (example items)

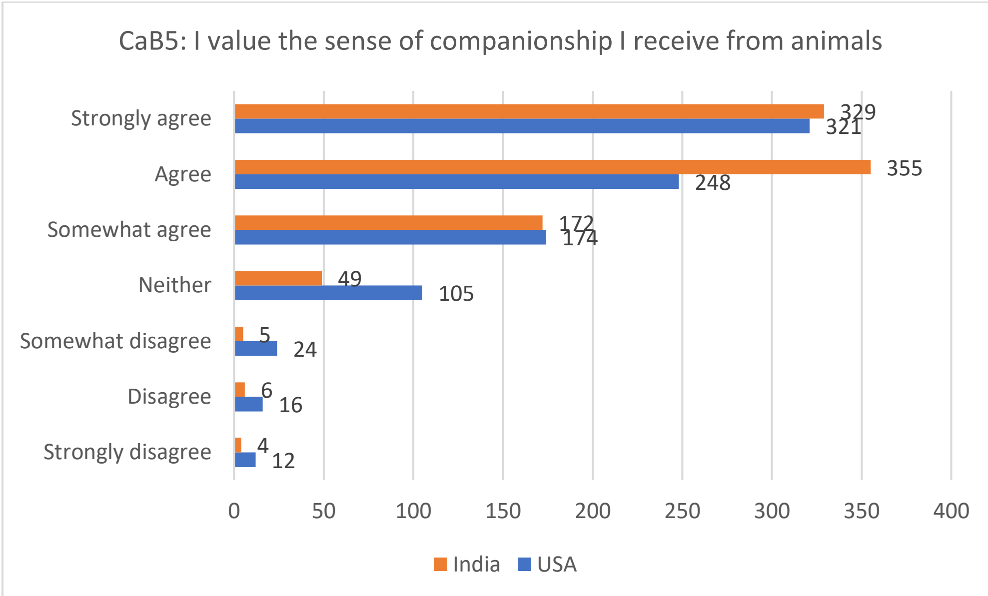

Figure 39 - Cross-national distribution of responses to CaB5

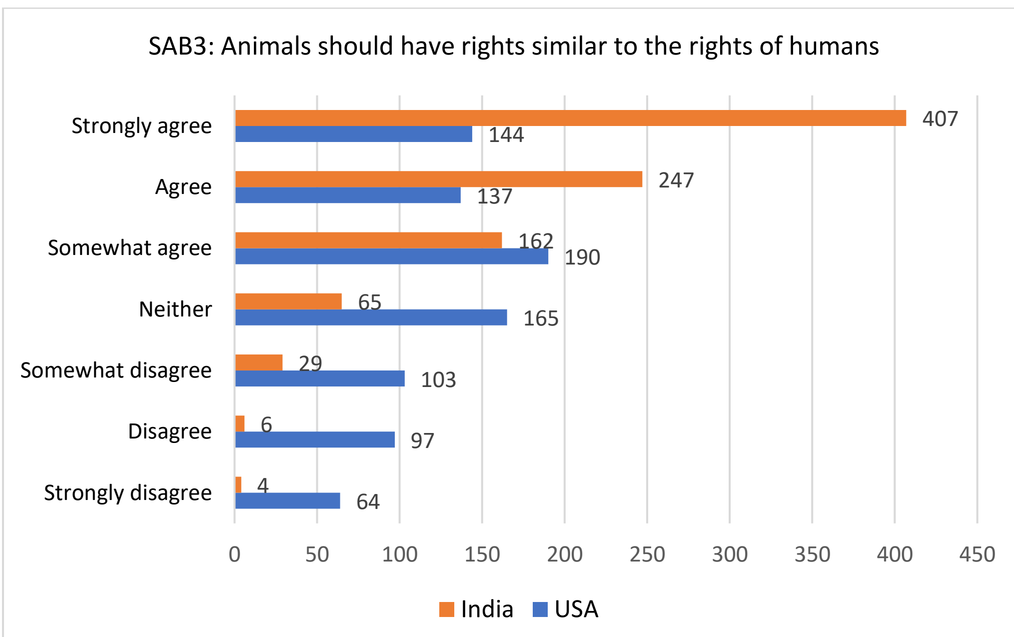

Figure 40 - Cross-national distribution of responses to SAB3

Awareness of Consequences

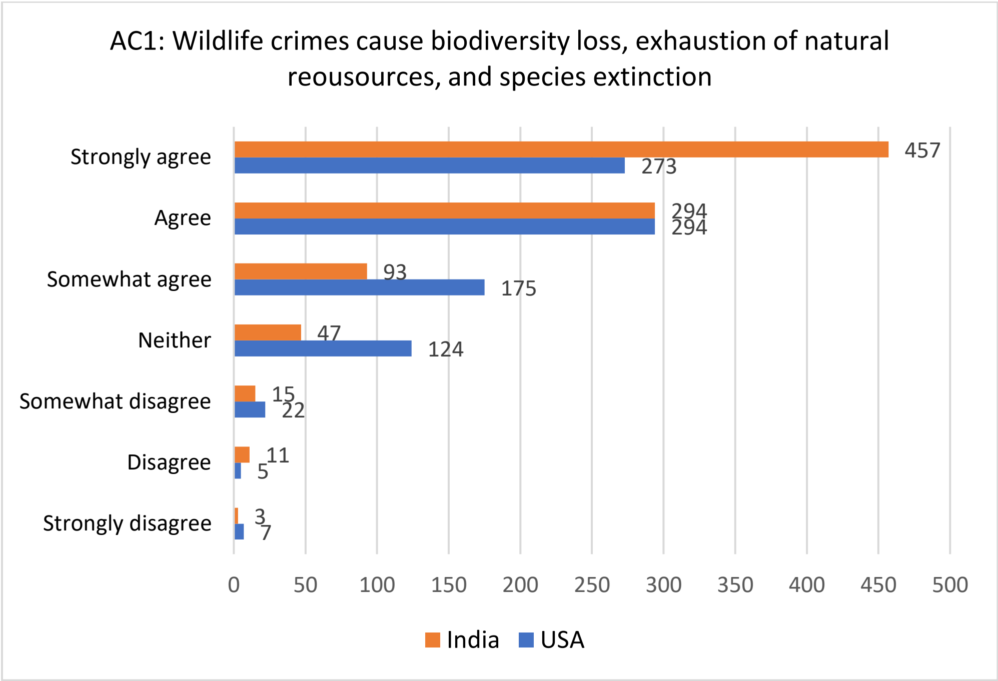

Figure 41 - Cross-national distribution of responses to item AC1

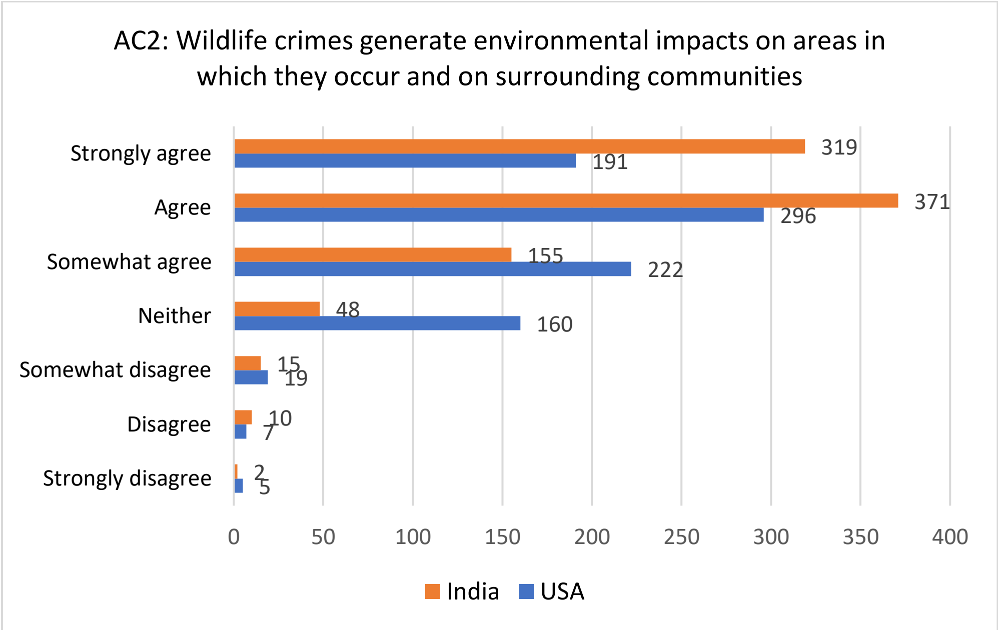

Figure 42 - Cross-national distribution of responses to item AC2

Figure 43 - Cross-national distribution of responses to item AC3

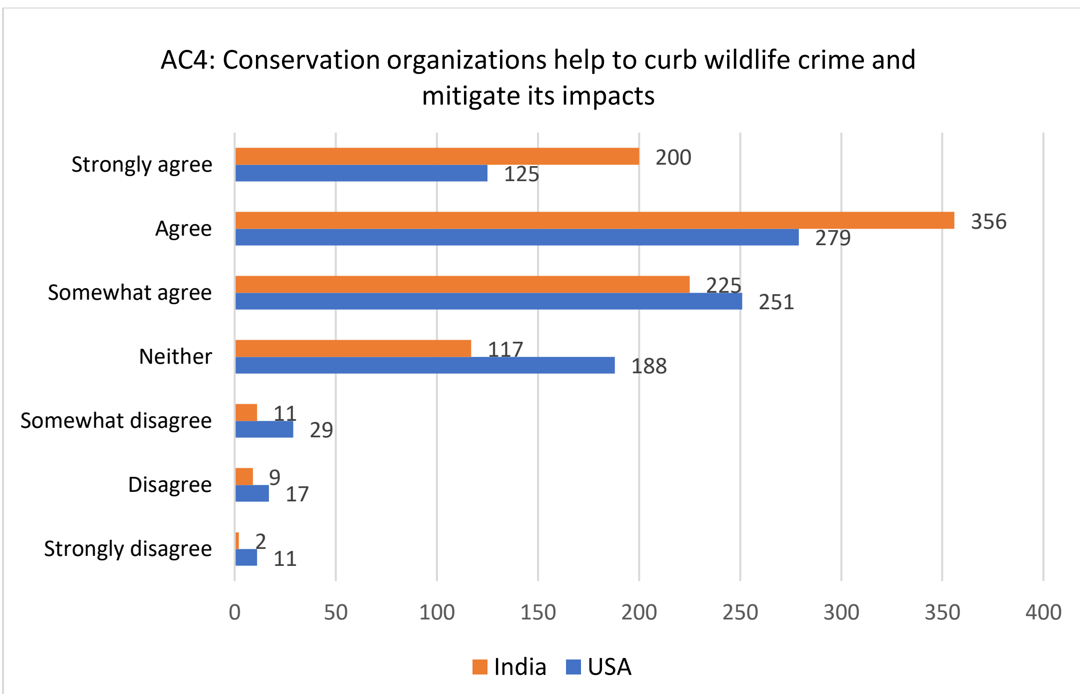

Figure 44 - Cross-national distribution of responses to item AC4

Ascription of Responsibility

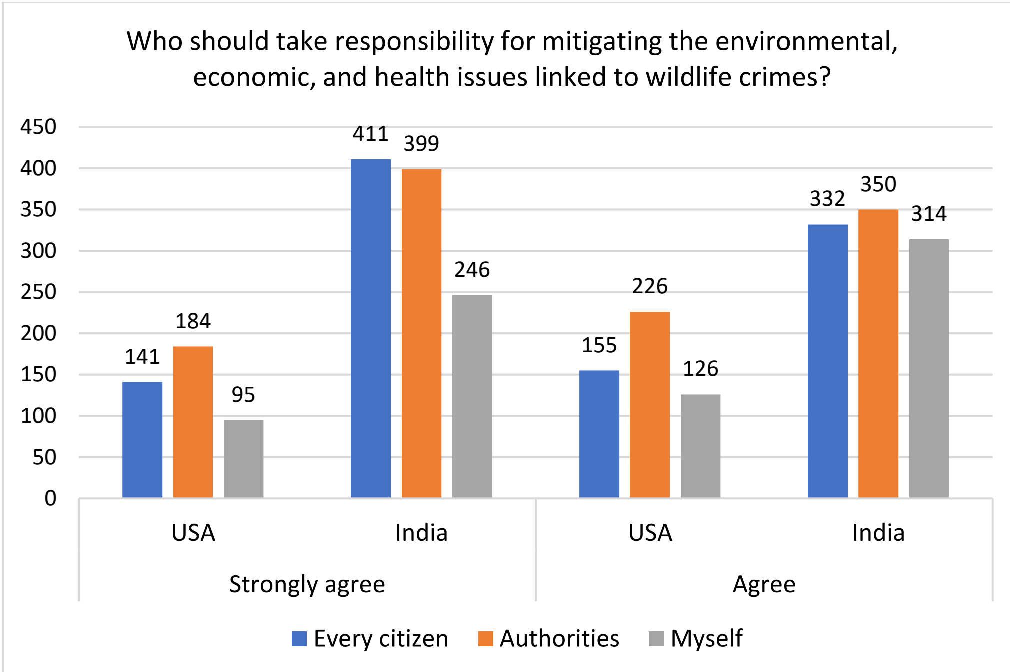

Figure 45 - Cross-national distribution of responses to ascription of responsibility items

Personal Norms

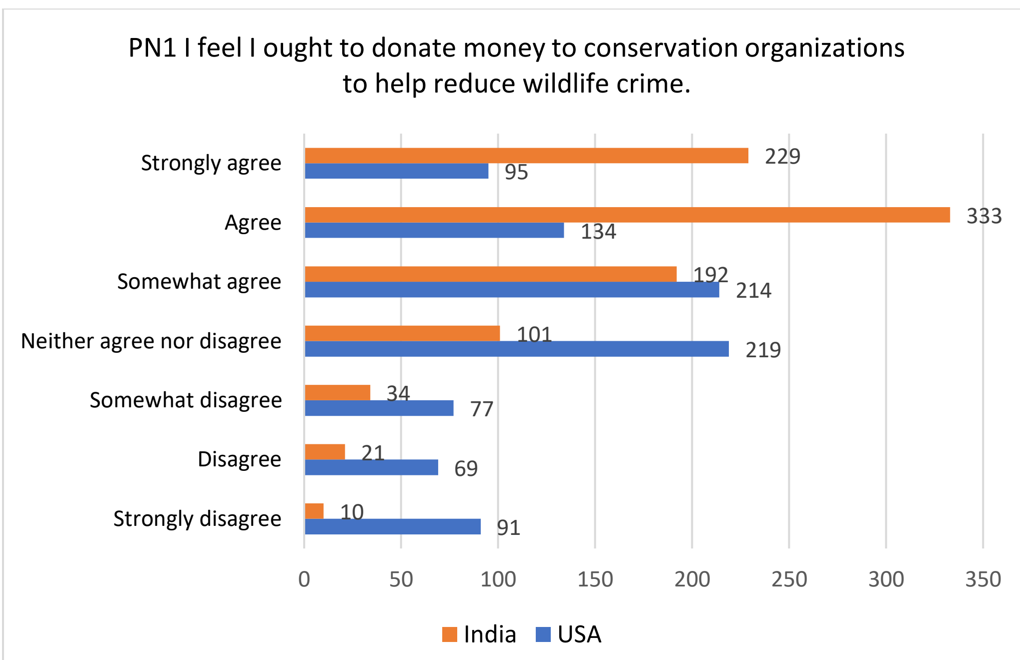

Figure 46 - Cross-national distribution of responses to item PN1

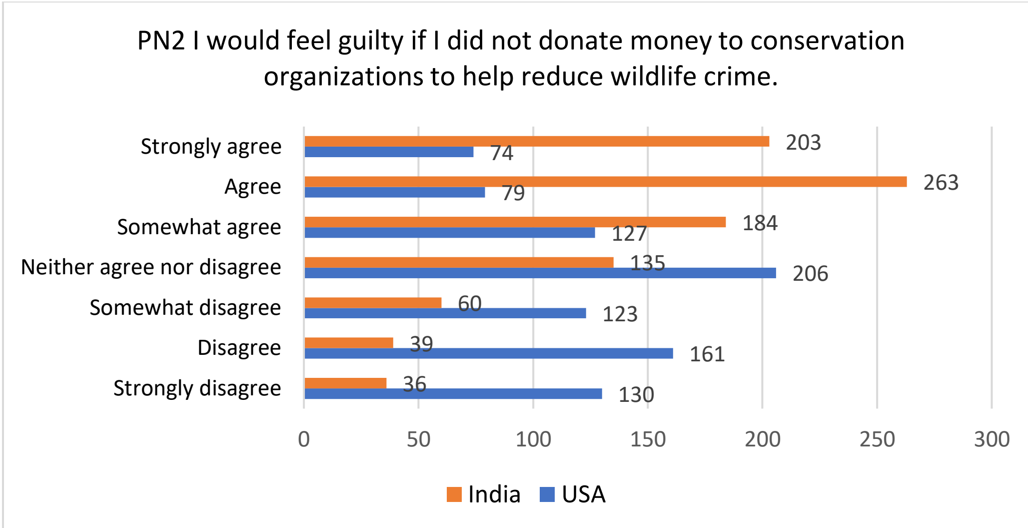

Figure 47 - Cross-national distribution of responses to item PN2

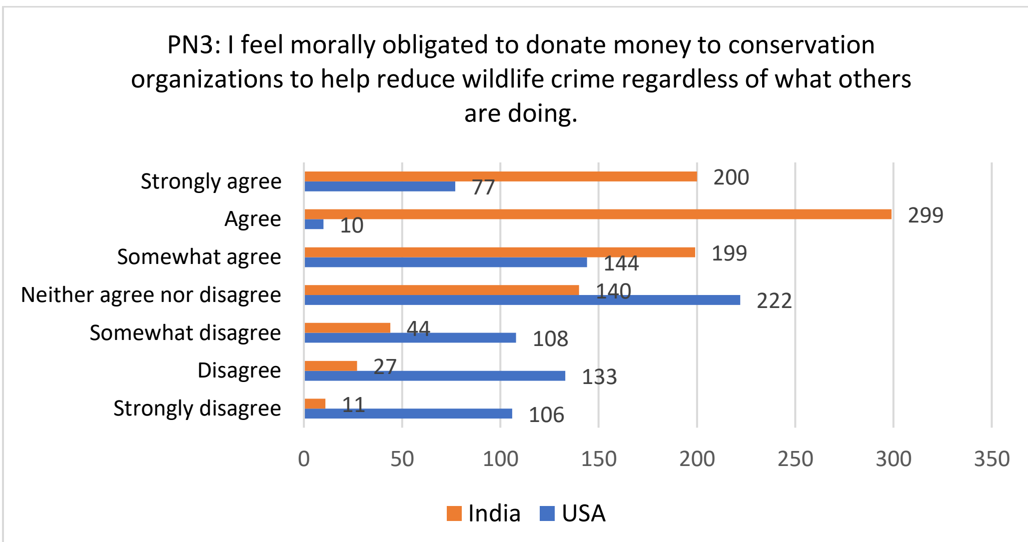

Figure 48 - Cross-national distribution of responses to item PN3

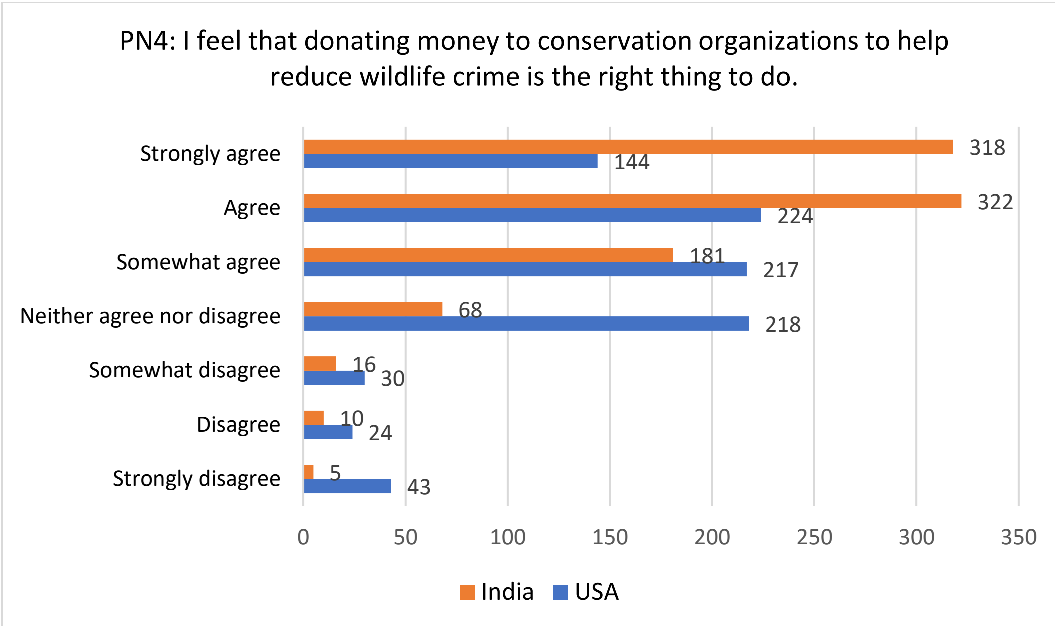

Figure 49 - Cross-national distribution of responses to item PN4

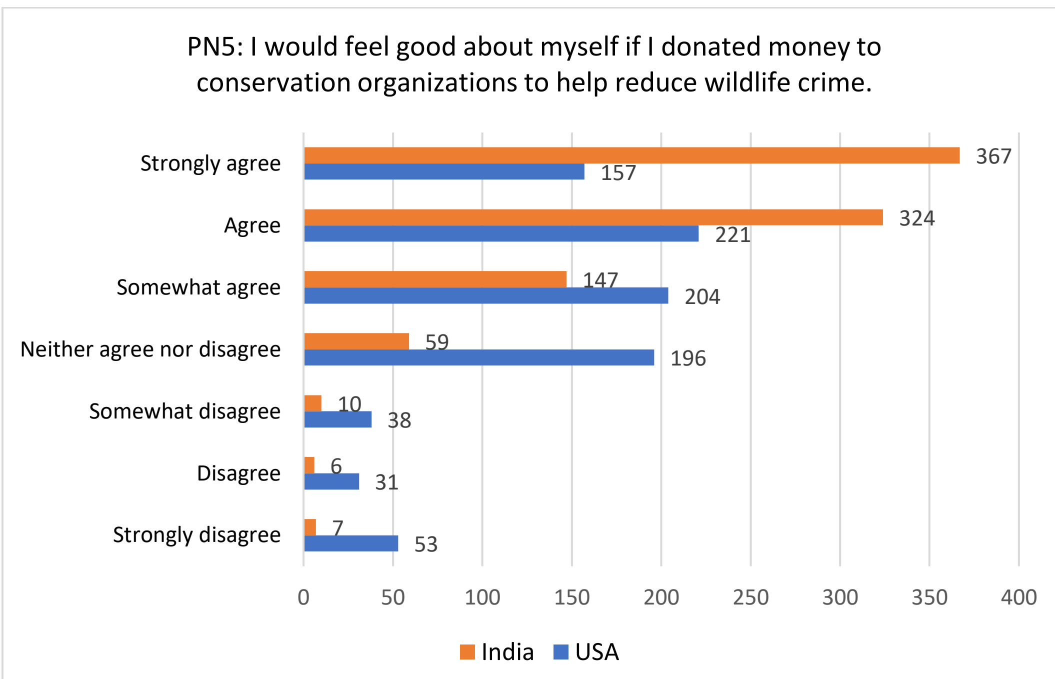

Figure 50 - Cross-national distribution of responses to item PN5