BEHAVIORAL ANTECEDENTS OF FUEL EFFICIENCY

DISSERTATION

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Abstract

"Energy is the lifeblood of the United States' warfighting capabilities."

- General David Petraeus, 2011

The US Department of Defense is the largest institutional petroleum consumer in the world. In addition to the financial cost of petroleum-based fuels, the US DoD generates more CO2-equivalent greenhouse gases than the entirety of modern, industrialized nations like Sweden and Norway. Other dangers and externalities arise from the fuels supply chain, like toxin risks to fuel handlers, and human costs to transport fuel in-theater. Within the DoD, the USAF alone often rivals or exceeds the consumption of all other services combined. While the USAF prefers technical, hardware-based solutions to problems, and has given increasing attention to logistical solutions like route planning and aircraft mix optimization, very little research both in and out of the military looks into the impact of human decision making on fuel consumption.

Industrial/organizational psychology, or "IO Psych," is a growing field in the civilian world. This project applies IO psychometric measurements to investigate the variability within fuel consumption stemming from the choices that human operators make. Three studies are presented, revolving around this common theme. These studies are based on the Theory of Planned Behavior (TPB), a behavioral science model emphasizing the kind of deliberate, informed decision making. The first study using meta-analysis indicates the TPB model strongly predicts fuel-efficient behavior. The second study examines car drivers' eco-friendly behavior. The results of the second study are congruent with the findings of the first study. The third study investigates the eco-friendly behaviors of military cargo pilots in the Air Force. Survey responses were collected from the population of 62 active duty, reserve, and Guard cargo airlift pilots flying the C-130, C-17, and C-5 platforms who flew a combined 477 cargo sorties within the measurement period. The pilots' responses were compared against a measure of fuel consumption corrected for change to cargo weight. The results of this study indicate that the link between intention and behavior is weak.

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I would like to express my sincere appreciation to my faculty advisor, Dr. Seong-Jong Joo, for his guidance and support throughout the course of this thesis effort. I would also like to thank Dr. Kenneth Schultz his support in the development of this research. Finally, I would like to thank my sponsor, Mr. Guerrero, from SAF-IE, for both the support and latitude provided to me in this endeavor.

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BEHAVIORAL ANTECEDENTS OF FUEL EFFICIENCY

I. Introduction

Sustainability is the responsible use of resources to support life, human and otherwise, in present and future generations. Framed more urgently, it must be a priority for current generations to ensure a livable world for their descendants (Oskamp, 2000). Our current world, hungry for energy, means that sustainable practices and policies are increasingly important. The growing global population looks forward to better standards of living, which means more worldwide energy consumption. All stakeholders in 21st century society depend on inexpensive energy to afford their standard of living, companies to maintain profitability and governments to control taxes.

The United States Air Force (USAF) uses $15B of fuel each year, more than all other Department of Defense agencies combined (USAF 2014, 30). The USAF records planned and actual fuel usage for each sortie flown. These data show that certain pilots tend to fly more efficiently than their peers. Why is this? What drives this behavior? A review of current literature reveals little research on discretionary pro-environmental behavior in a professional setting. This research uses the Theory of Planned Behavior as a starting point (Ajzen, 1985, 2011) to conduct a meta-analysis on pro-environmental transportation behavior in literature. Second, a TPB-based questionnaire developed by Cotton (2016) is administered to civilian personal vehicle operators and compared against self-reported measures of driving behavior. Finally, a population of USAF aircraft commanders was surveyed using this instrument, and the responses were plotted within a TPB model incorporating a measure of fuel efficiency on a per-sortie basis. The results should help us understand motivations as antecedents to fuel efficient behavior, setting the stage for future research into pilot motivations and encouraging energy-efficient behavior in professionals.

II. Literature Review

Theory of Planned Behavior

The Theory of Planned Behavior (TPB) is a behavioral science theory developed by Icek Ajzen (1985) which positions human behavior as a direct result of human intention towards that behavior. In turn, intention results from three antecedents: attitude towards the behavior, perception of social norms surrounding the behavior, and perception of one's level of control over enacting the behavior. The TPB differs from its direct ancestor, the Theory of Reasoned Action (TRA) (Ajzen and Fishbein 1980; Fishbein and Ajzen 1975) by the presence of this last psychological construct, perceived behavioral control (PBC). In many uses of the TPB, PBC has been shown to moderate the antecedent-dependent relationship between intention and behavior.

The Theory of Planned Behavior has been well supported by the body of literature because of its power in explaining and predicting deliberate, choice-based behavior. It regularly appears in literature surrounding pro-environmental behavior (PEB) studying individual and corporate behavior alike. Other behavioral models, like the norm-activation theory (NAM), overlap with the TPB in that they incorporate perceived social or personal norms, but struggle to explain or predict specific behaviors. In the case of our target population, USAF aircraft commanders (ACs), we wish to focus on deliberate decision making as the behavioral component of fuel efficiency.

Core Constructs

Intention: Intention (INT) is the sole direct antecedent of behavior in the TPB. Intention shares a positive relationship with behavior; the higher the level of intention to perform the behavior, the stronger likelihood exists that the subject will perform that behavior (Ajzen 1991). Intentions capture the motivational factors which influence behavior, and are therefore the necessary component of the TPB which allows explanation and prediction of specific rather than generalized behaviors (Ajzen 1991). As Ajzen is quick to point out, however, the motivational influence represented by Intention is only capable of predicting behavior if the subject is actually able to perform the behavior in question. Hindrances such as money, time, external cooperation, and in our case, aerodynamics (RAND 2015) represent actual behavioral control and can restrict the subject's ability to perform the behavior (Ajzen 1991).

Attitudes: Attitude in the TPB is defined as the "degree to which a person has a favorable or unfavorable evaluation" of a certain behavioral goal (Schifter and Ajzen 1985). The relationship between attitude and behavior is well studied in the literature, but attitude cannot predict behavior alone. Fishbein and Ajzen (1974) indicated that oftentimes, the existing models would fail to find a causal link, or even fail to find a relationship at all. However, they are quick to note that this cannot be taken as evidence of attitudes being wholly unrelated to behaviors (Fishbein and Ajzen 1974). Later additions to the theory would codify that the relationship is in fact mediated by intention, with attitude henceforth being positioned as an antecedent to intention (Schifter and Ajzen 1985).

Social Norms: Subjective Norm, often referred to as Social Norms, is the perception of social pressure in relation to the subject performing – or not performing – the behavior in question (Ajzen 1991). It can be thought of as the beliefs one holds towards other people's expectations whether or not to perform the behavior (Ajzen 1992). Subjective norm is a good predictor of intention to perform a behavior (Ajzen 1991).

Perceived Behavioral Control: If actual behavioral control represents the tangible restrictions surrounding the performance of behavior, perceived behavioral control (PBC) represents the ease or difficulty of performing the behavior of interest (Ajzen 1991). The emphasis here is on perception of factors directly linked with performing the behavior in question. PBC is sometimes positioned in the TPB literature as a direct antecedent to behavior (Ajzen 1991) or as a secondary or weaker antecedent to behavior (Ajzen 2012). Regardless, PBC demonstrates good predictive capabilities for intention (Ajzen 2001) and is generally measured by asking direct questions about capability to perform a behavior, or by indirectly asking about beliefs regarding inhibiting or facilitating factors (Ajzen 2002). PBC is strongly related to Bandura's (1977, 1982, 1986) concept of self-efficacy which influence human decision making, degree of effort put forth, perseverance, and thought patterns both positive and negative (Bandura 1986).

Additional Constructs and Antecedents, As Suggested by Literature

Habit: Habit as a construct is not included in the "core" TPB literature but many disparate studies argue in favor of its inclusion. In pro-environmental behavior literature, habit can appear as a force against which to be fought, exerting negative influences on

PBC and intention (Chen 2011). In other studies, habits are positioned as antecedents to behavior itself (Limayem et al. 2007; Klockner and Blobaum 2010; Klockner 2013; Lulfs and Hahn 2014). Lulfs and Hahn (2013), however, argue that habit exerts a moderating influence on the relationship between intention and behavior in the specific context of corporations exhibiting voluntary pro-environmental behavior (Lulfs and Hahn, 2013). The amount of variance concerning habits in the PEB literature indicates that habit may very well be specific to certain populations and must be evaluated through methods such as exploratory factor analysis (EFA) before any definite conclusions can be drawn.

Antecedents to Attitude. We include additional antecedents as predictors to the "core" TPB constructs of PBE, INT, ATT, SN, and PBC.

Environmental Concern. We position environmental concern as an antecedent to ATT, rather than as a direct antecedent to PEB, due to the literature indicating the construct works better in a supporting role rather than in a direct role. Many studies in the past have demonstrated a link between environmental awareness and pro-environmental behavior, but often this link is weak. Grob (1995) investigated this relationship via path analysis and found its strength to be 0.1. Onwezen et al. (2013) took an approach based in the norm-activation model (NAM), eschewing the direct causal relationship in favor of positioning awareness behind "responsibility" and "personal norm" constructs. In a supporting role rather than a direct role, environmental awareness performed considerably better, able to predict "responsibility" with a path coefficient of .712. By contrast, Onwezen (2013) still only observed correlations of .289 and .247 between awareness and two types of pro-environmental behavior (purchasing behavior and travel behavior, respectively). Based on Dunlap and Van Liere (1978) and Dunlap et al. (2000), the New Environmental Paradigm (NEP) is the most widely used measure of an individual's environmental concern. The NEP demonstrates good internal reliability with an American audience (Schultz and Zelezny 1998). The NEP, in our usage, seeks to capture the variance that environmental concern may contribute to an individual pilot's attitudes towards fuel-efficient flying.

Efficiency vs. Effectiveness. While pro-environmental behavior research in a military context is scarce, certain studies indicated a certain perception that PEB carries with it inherent tradeoffs in mission effectiveness. In an industrial/organizational context, Cagno et al. (2013) cite "lack of power and/or influence by people in charge of energy management" as an organizational barrier to energy-efficient behaviors. Our proposed attitude antecedent which believes that "the mission" will be compromised by performing pro-environmental behaviors is grounded in Ciarcia (2013). Ciarcia (2013) focuses on Marines asked to adopt newer and more efficient technologies in the field. A strong barrier to such adoption was found to be perceptions that the technology's purpose, being primarily about efficiency and eco-friendliness, would weaken the troops' overall ability to complete the mission. These such beliefs prompted us to investigate the presence of similar attitude antecedents in our study, hence the conception of Efficiency vs. Effectiveness (EVE) as distinct from perceptive factors such as PBC-SE or PBC-CN. Our items have been coded such that higher scores on EVE indicate less of a belief that PEB will weaken the mission.

Pride in Performance. We hypothesize that pilots who believe that saving fuel while flying represents their mastery of the aircraft will be more likely to report more positive attitudes towards saving fuel while flying. In addition, we hypothesize that pilots who believe that saving fuel while flying represents their mastery of the aircraft will be more likely to report more positive attitudes towards flying at maximum-range airspeed.

Organizational Citizenship Behavior. We hypothesize that pilots who report higher levels of organizational citizenship will be more likely to report more positive attitudes towards saving fuel while flying. In addition, we hypothesize that pilots who report higher levels of organizational citizenship will be more likely to report more positive attitudes towards flying at maximum-range airspeed.

Energy Security. We hypothesize that pilots who report higher levels of concern for the energy security of the United States will be more likely to report more positive attitudes towards saving fuel while flying. We also hypothesize that pilots who report higher levels of concern for the energy security of the United States will be more likely to report more positive attitudes towards flying at maximum-range airspeed.

Maximize Options. We hypothesize that pilots who report exercising caution against unplanned in-flight events will be more likely to report more positive attitudes towards saving fuel while flying. We also hypothesize that pilots who exercising caution against unplanned in-flight events will be more likely to report more positive attitudes towards flying at maximum-range airspeed.

Antecedent to Subjective Norm: Organizational Emphasis (OE). In a strict hierarchy like the USAF, one's social climate can be altered by directives and emphases from those in command. Here, we define OE as the perception of social pressure arising from those above the squadron-level, i.e. group or wing level decisions, Air Staff, etc. The squadron is the most tight-knit of the organizational levels and therefore the best fit for measuring SN; thus, OE must be defined as external to the squadron, and higher up the chain of command than the squadron commander. We hypothesize that pilots who report higher levels of organizational emphasis are more likely to report higher levels of perceived social pressure within their squadron.

III. Original Contribution

The first article represented a novel attempt for conducting multivariate meta-analysis of eco-friendly personal transportation behavior using meta-analytic structural equation modeling (MASEM). The procedure involved collecting correlation matrices from studies on personal transportation behavior within the TPB framework and analyzing them using the MASEM method.

The second article utilized TPB to investigate behavioral antecedents of eco-driving within a civilian population. Measures of subjective norms, attitudes towards fuel efficiency, attitudes towards moderating highway speeds, self-efficacy of saving fuel, and controllability of fuel consumption were developed, tested, and modeled. Results conformed to past TPB research in ecological psychology literature; namely, that the TPB provided a useful framework for explaining eco-driving behavior.

The third article synthesized the findings from the first two articles and, together with a TPB-based survey instrument developed by Cotton (2016), studied a novel target population of USAF aircraft commanders. This represents, to the best of the researchers' knowledge, the first instance of behavioral research applied towards studying subjects with such a high potential individual impact on fuel consumption. Support was found for the TPB but results indicate that further research is required.

IV. Journal Articles

Paper 1: Examining Eco-Friendly Personal Transportation Behavior: A MASEM Approach

Introduction:

Personal transportation choices aggregate into large environmental impacts. Human desire for mobility does not exist in individual-specific vacuums, each person's choices impact everyone else. Personal vehicles burning petrochemicals contribute a major portion of transportation-caused pollution (Black, 1996). Global passenger demand projected for the year 2100 indicates a fivefold increase vs. 2000, with transportation energy use increasing by a factor of three, and CO2 emissions by a factor of 2.5 (Girod et al., 2013). Furthermore, transportation accounts for considerable environmental damage even beyond the local area. The 1997 signing of the Kyoto protocol asked the most heavily polluting countries to reduce their greenhouse gas contributions to climate change (Chapman, 2007). Oil accounted for 97 percent of fuel use in the transportation sector while road-going transportation (light passenger vehicles and commercial trucking alike) accounted for 81 percent of transport modes (Chapman, 2007).

Carpooling, and public transportation are examples are the many types of pro-environmental personal transportation behavior. Carpooling, the sharing of one vehicle among multiple passengers, can reduce environmental impact despite being less efficient than public transit. Minett and Pearce (2011) conducted a study on 9000 "casual" carpoolers in San Francisco which estimated it saved between 0.45 – 0.9 million US gallons of fuel in a year. Casual carpooling operates on an informal queue system similar to taxi stands, where drivers take on enough passengers to allow them access to the high-occupancy vehicle (HOV) highway lanes. The practice has drawn some criticism for passengers choosing to carpool rather than use bus or rail, which are considerably more efficient (Minett and Pearce, 2011). In a normal San Francisco practice, which includes a mix of bus and single occupant vehicle (SOV) usage, however, the casual carpool system still saves energy. The bus and SOV combination uses 24 percent more energy than an equivalent passenger load carried by casual carpooling, making casual carpooling attractive as a first step (Minett and Pearce, 2011). To the individual, carpooling is attractive to commuters primarily due to economic factors, followed by environmental concerns and comfort as second and third factors (Ciasullo et al., 2018).

The Theory of Planned Behavior (TPB), codified by Ajzen (1991), has been used to explain how consciously chosen behaviors result from positive intentions towards those behaviors. In turn, intentions result from attitudes, perceptions of social norms, and perceptions of behavioral control. The TPB has strong support for predicting generalized pro-environmental behaviors, as previous meta-analyses have noted (Bamberg et al., 2007; Klöckner, 2013). To the researchers' knowledge, however, there has been no meta-analysis focusing solely on TPB literature studying pro-environmental transportation behavior (BEH). This study therefore conducts a systematic literature review on the TPB and employs two-stage structural equation modeling (TSSEM) to paint a comprehensive overall picture of the state of pro-environmental transportation behavior.

This study's findings indicate that the TPB model is strongest when including the antecedent-dependent relationship between perceived behavioral control (PBC) and BEH, even if the relationship itself is weak. This finding supports previous studies such as

Kaiser and Gutscher (2003), who argued that the ability of PBC to directly predict BEH depended on the specificity of the behavior measured by the BEH construct. With a high specificity of BEH (a specific population cycling to work at a specific time, for example), the PBC-BEH relationship was stronger. With a low specificity of BEH (generalized "pro-environmental behaviors" encompassing everything from curbside recycling to eco-driving to sustainable purchasing) the strength of the PBC-BEH relationship wanes. The strength of the PBC-BEH relationship (0.12) was found to be comparable to that found by Klöckner 2013 (0.11), despite this study conducting a more focused search.

Theory of Planned Behavior and Transportation:

The TPB was developed by Ajzen and others over several studies (Fishbein and Ajzen, 1974; Ajzen and Fishbein, 1977; Schifter and Ajzen, 1985) and codified in "Theory of Planned Behavior" by Ajzen (1991). The TPB model is based on the mediating relationship that INT (Intention) plays between BEH (Behavior) and three motivational factors – ATT (Attitude), PBC (Perceived Behavioral Control), and SN (Subjective Norm). The TPB models behavior as an outcome of deliberate decision making. This deliberate decision making is expressed in the antecedent-dependent relationship between one's intention to perform a behavior or INT, and one's actual behavior or BEH. The TPB is summarized in Figure 1.

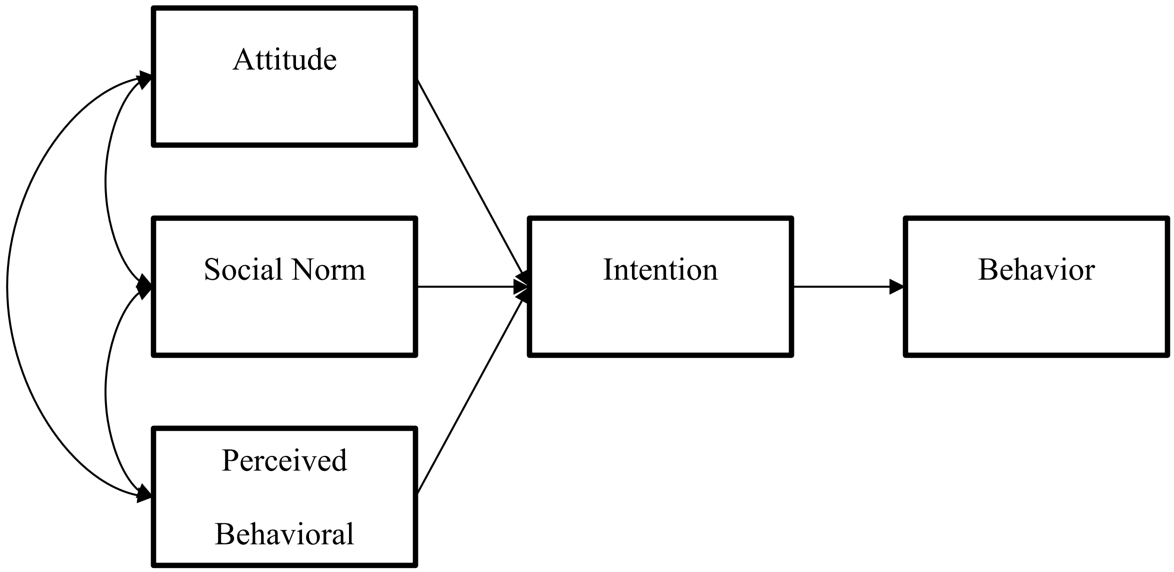


Figure 1: Theory of Planned Behavior (Ajzen, 1991).

Behavior (BEH) in this paper includes multiple types of eco-friendly transportation behavior such as walking, riding bikes, using public transport, carpooling, and driving in a fuel-efficient manner. Synthesizing these behaviors is important because combinations of strategies for behavior change are often more successful (Steg and Vlek, 2009), and doing so enables a greater diversity of commuting types for capture. The inclusion of car-based behaviors like carpooling and eco-driving allows the results of this study to be useful to more than just individuals who live in the city with abundant transportation options.

The TPB holds Intention (INT) as the strongest predictor of behavior, accounting for a quarter of behavioral variance (Steinmetz et al., 2016). The strength of intention is such that experimental interventions designed to motivate individuals to perform specific behaviors will be superfluous if the individual already intends to perform the behavior (Steinmetz et al., 2016.

The Attitude construct (ATT) encompasses the behavioral beliefs governing favorable or unfavorable personal attitudes towards the behavior in question (Ajzen, 2012). Attitude can also be comprised of beliefs about consequences; belief in positive consequences lead to a more positive attitude and vice versa (Steinmetz et al., 2016).

Subjective Norm (SN) represents the normative effect upon behavioral intentions produced by the perceived social pressure to perform the behavior in question (Ajzen, 2012). A favorable social norm can foster an individual's intention to behave a certain way, just as an unfavorable social norm can hinder it. For example, behavioral change interventions conducted in public, or in a group setting, are often more influential than interventions conducted in private settings or only focusing on individual subjects (Steinmetz et al., 2016).

Perceived Behavioral Control (PBC) represents control beliefs, which are beliefs regarding factors which may help or hinder the individual's performance of the behavior in question. These can take the form of resources or helping and obstacles or hindering (Ajzen, 2012). The "expanded" TPB includes a relationship where PBC influences BEH. This can represent situations where control beliefs bypass intention. In such situations, argues the expanded TPB model, attention spent on providing resources or removing obstacles can result in performance of the desired behavior (Steinmetz et al., 2016).

Previous meta-analyses have indicated the TPB has strong explanatory and predictive capability in the realm of pro-environmental behavior (Bamberg and Schmidt, 2001; Bamberg, 2006; Bamberg and Möser, 2007; Bamberg et al., 2007). They have found strong support for TPB's core concept of INT mediating ATT, PBC, and SN relationships to BEH and suggest that the TPB performs better with the addition of personal moral norms or PMN. Some studies approach the TPB from the standpoint of incorporating the norm-activation model (NAM), which provides strong evidence that PMNs play a role in eco-friendly behavior (Klöckner et al., 2003; Klöckner and Matthies, 2004; Matthies et al., 2006; Klöckner and Matthies, 2009; Klöckner and Ohms, 2009; Haustein et al., 2009; Klöckner and Blobaum, 2010; Klöckner and Friedrichsmeier, 2011; Klöckner, 2013; Klöckner et al., 2013). Klöckner (2013) performs a meta-analysis of pro-environmental behavior in general, and places PMN as an antecedent to INT, similar to ATT, SN, and PBC. Other studies suggest that including a personal-norm model like the NAM is not strictly necessary for modeling pro-environmental behavior. In a meta-analysis study spanning behavioral disciplines, Lanzini and Khan (2017) find habits and past behavior to be relevant predictors of travel mode choice. Schoenau and Müller (2017) suggest that external costs are a much stronger predictor of transportation-related pro-environmental behaviors than INT. Yang-Wallentin et al. (2004)'s meta-analysis indicates that, for the specific behavior of travel mode choice, PBC is a moderately strong predictor of BEH.

It is important to frame the decision to use sustainable transport options in terms of actual and perceived feasibility (PBC). The personal motor vehicle may be an inefficient mode of transport, but city sprawl and suburban development often leave scarce alternatives. In much of the United States, individuals live in suburban communities, where on average they consume twice as much land as urban dwellers and drive 31 percent more (Kahn, 2000). The more convenience commuters must sacrifice to choose an environmentally friendly mode of transportation, the less feasible that mode becomes. Antecedents of the decision to walk or cycle instead of drive include neighborhood environmental factors such as city density, safety, and presence of dedicated bike or walking paths; individual factors include car ownership, income, age, and gender (Saelens et al., 2003). Individuals will evaluate transportation options available, and oftentimes the convenience of personal car use outweighs more abstract factors like environmental impact. These factors contribute to the greater environmental damage incurred by growth of suburban living vs. living in cities, despite mitigating factors like increased car and truck fuel efficiency (Kahn, 2000).

Pollution can motivate wealthier individuals to eschew city life in favor of the more resource-hungry suburban life. Prior research has indicated a link between fine particulate emissions, often from diesel engines, and mortality in urban dwellers (Ostro et al., 2007; Cao et al., 2012). This quality of life impact is often felt by historically underprivileged communities of low-income individuals and ethnic minorities (Miranda et al., 2011). Mean diesel particulate exposure, principally from highways where heavy trucking occurs, was 38 percent higher for minorities than for whites in a California city center, a quality of life impact of 14 days' shorter lifespan on average, translating into 370,000 years when multiplied by the 9.8 million individuals in the study area (Nguyen and Marshall, 2018). This process contributes to a feedback loop of wealthier, mainly white individuals and families choosing suburbs over cities, while their commutes into the city exacerbate the issues with pollution (Miranda et al., 2011). Specific strategies targeting diesel particulate emissions, like low-emission zones and diesel truck rerouting, have been shown to reduce overall exposure to these pollutants in largely minority residents (Nguyen and Marshall, 2018).

Most examples of pro-environmental behavior in TPB literature involved personal recycling efforts or green purchasing options (e.g. purchasing energy-efficient appliances). Although there were studies which investigated green purchasing behaviors as applied to personal transportation, such as plugin-hybrid electric vehicle (PHEV) adoption (Adnan et al., 2017; 2018) or vehicles with smaller engine displacements (Qu et al., 2014), those studies were not included in order to place the focus on everyday use of personal transportation rather than a one-time purchasing decision. The TPB has shown success in application to other transportation related behaviors beyond eco-friendly transportation, such as drinking and driving, risky overtaking, poor lane discipline, and dangerous pedestrian conduct (De Groot and Steg, 2007).

The objective of this study is to summarize the current body of TPB literature dealing with eco-friendly transportation behaviors, and to test the strength of relationships between core TPB constructs in this regard. To look at the spectrum of eco-friendly transportation behaviors is to incorporate studies which focus on modes of transit such as bicycling, rail, bus, and walking. In addition, studies which focus on the antecedents to personal car use, single-occupant vehicles, reduction in car use, and carpooling behavior are also relevant. Studies such as Abrahamse et al. (2009) link the decision to use a car for commuting to beliefs of individual outcomes, such as PBC and ATT. Some studies include habit as a construct. Habit, often conceptualized as past behavior or autonomous decision making, has been shown to set boundary conditions for deliberate decision making. External pressures such as incentives which are geared to stimulate conscious rather than habitual decision making find their efficacy operating only within the bounds of habit (Verplanken et al., 1998). However, in the studies reviewed for this meta-analysis, habit was inconsistent in its placement as a predictor and was therefore excluded.

The decision to use MASEM enables a multivariate perspective for this study because it does not restrict searches to only testing one univariate relationship at a time. Bamberg and Möser (2007) found MASEM works well to model psychosocial determinants of pro-environmental behavior, with the ability to explain 27 percent of the variance of pro-environmental behavior in studies analyzed. Coding each study as a correlation matrix means that studies which look at some relationships but not others (e.g. INT and its antecedents, but not the relationship between INT and BEH) can be included where meta-analyses testing the single relationship could not.

This study addresses three research questions. First, this study investigates the efficacy of measuring eco-friendly behavior on personal transportation within the TPB. Second, this study tests the strength of the relationships among constructs using multivariate meta-analysis structural equations modeling (MASEM) approach. Third, this study tests three different models: the TPB without correlations between independent constructs, the TPB model that includes those correlations, and the TPB model that adds the correlations and a direct relationship between PBC and BEH.

Method:

The first step was to search the literature for eligible studies. First, a keyword search was performed upon the following databases: EBSCO Discovery; Google Scholar; American Psychological Association Database. The keywords used during this first phase were as follows: (“eco-friendly behavior” AND “intention”) OR (“eco-friendly” AND “behavior” AND “intention”) OR (“theory of planned behavior” AND “environmental”). Results were saved and recorded into a database to eliminate duplicate results. Of 1,124 raw keyword search hits, 58 studies were relevant, and 13 studies were useful. One study included a correlation matrix with more than five (one third of lower diagonal) missing cells and was excluded. Of the remaining 12 studies, 6 were missing correlations between constructs and the author(s) were emailed to request these correlations.

Backward searches were performed on results which fulfilled the criteria of: using the TPB; studying pro-environmental behavior, and studying transportation related behavior. In particular, previously published collections of articles were consulted during backward searches. The results of the first round of backward searches yielded three studies, two of which were missing correlations between constructs. The remaining study was coded into the database, and between-construct correlations were requested from the authors of the other two studies via email.

The following meta-analyses were examined during the backward search process, and relevant studies from their pool were used: Yang-Wallentin et al. (2004), Bamberg and Möser (2007), Gardner and Abraham (2008), Klöckner (2013), Bamberg and Rees (2017), Lanzini and Khan (2017), and Chng et al. (2018). Of 36 relevant studies encountered from mining previous meta analyses and literature syntheses, 20 studies supplied correlations between constructs. Of those which provided correlations, seven studies had five or more missing elements, leaving 13 studies to be coded. 16 studies did not, and their authors were emailed to request correlations between constructs.

A forward search was performed via the same databases consulted in the keyword search, as well as the databases used during the table-of-contents searches. The forward search yielded 15 studies, eight of which provided correlations between constructs. Of those, three studies had five or more missing elements and were rejected, leaving five studies to be coded. The authors of the seven studies without between-construct correlations were emailed to request them.

The final search was a table-of-contents search, which was performed on the following major journals: *Journal of Cleaner Production*; *Transport Policy*; *Transportation Research Parts A, D, E,* and *F*; *Production and Operations Management Society* (POMS), *Journal of Operations Management* (JOM), *Journal of Environmental Psychology*, and *Travel Behavior and Society*. This search was performed by accessing each journal's table of contents and individually opening each issue for relevant papers. 22 studies included between-construct correlations, although of those 22, nine studies were unusable due to having five or more missing elements in the correlation matrix. This procedure left 13 studies to be coded into the meta-analysis. 47 studies were missing between-construct correlations and their authors were emailed with requests.

In total, there were 78 studies which were relevant to this meta-analysis but did not include correlations between constructs. Each available author was emailed a request for between-construct correlations with a cutoff date set of 5 September 2019. 16 responses were received before the cutoff date. Of those responses, one study (Klöckner et al., 2013) became usable, while two studies' responses provided data that fell within the exclusion criteria.

Selection and exclusion criteria:

The raw number of studies is simply the total number of search hits. Those studies which were not peer reviewed were then filtered out. To be considered in the correct field, studies needed to use the Theory of Planned Behavior and specifically look at Pro-Environmental Behavior (BEH) and/or its antecedents (INT, ATT, PBC, and SN). This is where the process as shown in Figure 2 begins. Relevant studies were those which fit the criteria above, and were relevant to the topic of discretionary pro-environmental transportation behavior. They moved into "Usable" if they measured a statistically valid sample size and generally adhered to the TPB structure without making drastic rearrangements. Each study reported Pearson's correlation (*r*) between at least two of the core five TPB constructs of BEH, INT, ATT, SN, and PBC. If a study looked at multiple types of the same construct such as BEH, and/or studied multiple separate populations, each unique instance of BEH was coded as its own five by five (5x5) correlation matrix.

Studies which reported intention (INT) pointing towards BEH, but without reporting BEH itself, were also considered so long as they met the criteria above (e.g., de Groot and Steg, 2007). The same is true for other constructs studied, so long as they were applicable to the TPB (e.g., Setiawan et al., 2014; Chen, 2016). Finally, each study could have no more than five missing data elements. The lower-diagonal elements of a 5x5 matrix includes fifteen cells that can contain data: five down the diagonal where each construct intersects with itself, and ten below the diagonal where each construct intersects with each other construct once. Studies that only reported on one relationship (e.g., the relationship between ATT and BEH only, thus, missing all others) could skew the data analysis with undue emphasis on that one relationship. Therefore, a maximum of one third of the potential data (five missing cells) were permitted, so as not to exclude studies omitting a single construct. Two variants of *n* were taken into account: number of studies found to match the selection criteria were total 40, and number of usable matrices within studies were total 63. The process for selection and exclusion is detailed in Figure 2.

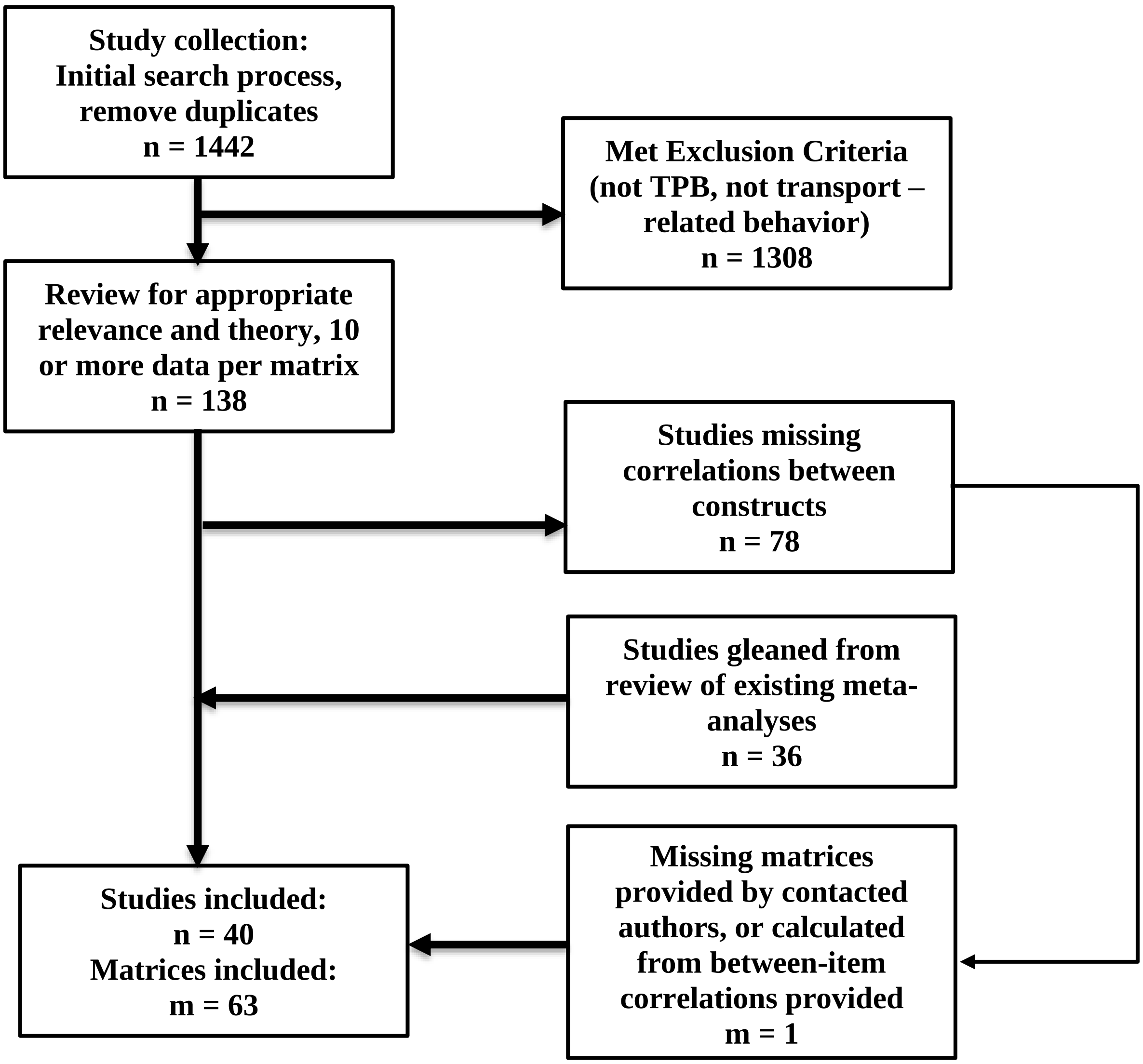


Figure 2: Flow Chart for the Sampling Process.

3.2 Coding of the studies

Studies were coded into Excel with a 5x5 matrix containing inter-construct correlations between BEH, INT, ATT, PBC, and SN in descending order (horizontal and diagonal). For each study, we recorded the designator code, authors, theory, sample size, field, location studied, journal published, year published, date the study was coded, and researcher who coded the study. Inter-construct correlations were coded below the diagonal of each matrix.

Studies reporting multiple correlations of the same construct, such as different types of BEH, were coded as unique matrices for each combination of relevant constructs. For example, Erikkson and Forward (2011) reported three different correlations on BEH: car use, bus use, and bicycle use, and the BEH correlation matrices were coded respectively. If a study reported the same constructs via different samples, each separate sample was coded as its own separate matrix. In de Groot and Steg (2007), INT to commute via public transportation was compared between travelers commuting to shop and travelers commuting to work in a certain area. These were coded as two separate matrices to capture the different samples studied.
Each study was identified with a numerical code indicating which search it came from.

Each study is identified with a numerical code indicating which search step it came from (Study ID, Table 1.) Studies beginning with the numbers 1, 2, 3, and 4 came from the four database searches. Studies numbered 5 or 6 came from backward searches. Studies numbered 7 came from other meta-analyses (Yang-Wallentin et al., 2004; Bamberg and Möser, 2007; Klöckner, 2013; Lanzini and Khan, 2017). Studies numbered 8 were found from forward searches of works which had cited studies previously encountered in the correct field. Seven relevant studies were found and five studies proved usable. Studies numbered 9 came from table-of-contents searches.

The final search result includes 40 independent studies with 63 usable correlation matrices, with $N_{subjects}$ of 28,326 and $N_{sampling}$ of 39,307. One study was excluded from the fixed-effects model due to having a non-positive-definite correlation matrix. Therefore the fixed effects model included 39 independent analyses, 62 correlation matrices, $N_{subjects}$ of 28,210 and $N_{sampling}$ of 39,191. Table 1 displays the studies incorporated into this review and classifies them by the type of eco-friendly transport behavior studied and by country.

Study ID	Authors	Year	Study Description	Behavior	Country
315a	Huang et al.	2018	Measuring mediating role of INT on antecedents of BEH, measuring moderating role of planning on INT-BEH relationship	PT	Australia
327	Chen et al.	2017	Exploring moderating effect of residential area on travel mode choice	CU	China
360	Lauper et al.	2015	Investigate predictors of eco driving from the perspective of road noise	ED	Switzerland
366	Gardner & Abraham	2010	Testing TPB model of car use vs. non-car use from environmental standpoint	CU	United Kingdom
398	Abrahamse et al.	2009	Investigate effect of self-interest variables and moral considerations on reducing car use, within TPB model	CU	Canada
412c	Harland et al.	1999	Behavior change intervention on multiple environmentally friendly behavior categories	CU	Netherlands
501a	Bamberg et al.	2007	Testing TPB model of processes mediating the effects of personal norms over two populations (Frankfurt sample)	PT	Germany (Frankfurt)
501b			Testing TPB model of processes mediating the effects of personal norms over two populations (Dortmund sample)	PT	Germany (Dortmund)
707	Heath & Gifford	2002	Behavior change intervention on effect of universal bus pass on prediction of public transport use by TPB model	PT	Canada
720a	De Groot & Steg	2007	Testing TPB model to explain park-and-ride facility use by shoppers	PT	Netherlands
720b			Testing TPB model to explain park-and-ride facility use by workers	PT	Netherlands
734	Kerr er al.	2010	Testing addition of habit to TPB model to predict car use by students	CU	Australia
741b	Klöckner et al.	2013	Investigating effects of electric vehicle purchase on car use	CU	Norway
743	Bamberg & Schmidt	2010	Effect of behavior change intervention (prepaid bus pass) on TPB constructs of ATT, SN, PBC, INT, and BEH	PT	Norway
745a	Eriksson & Forward	2011	Compare predictors of INT towards reducing car use	CU	Sweden
745b			Compare predictors of INT towards use of public transport	PT	Sweden
745c			Compare predictors of INT towards use of bicycle	BK	Sweden

748a	Haustein & Hunecke	2007	Investigate moderating effect of perceived mobility necessities on car use INT	CU	Germany
748b			Investigate moderating effect of perceived mobility necessities on public transport INT	PT	Germany
748c			Investigate moderating effect of perceived mobility necessities on bicycle use INT	BK	Germany
750	Hsiao & Yang	2010	Testing addition of additional antecedents (Novelty, Trust) on TPB model of students' decisions to use high speed rail	PT	Taiwan
757a	Lo et al.	2016	Comparing effects of commute length on travel mode choice (Short commute)	CU	Netherlands
757b			Comparing effects of commute length on travel mode choice (Long commute)	CU	Netherlands
758	Lois et al.	2015	Testing addition of social identity to TPB model to predict bicycle use	BK	Spain
760a	Mann & Abraham	2012	Testing TPB constructs of INT, ATT, PBC, and SN on predicting car use	CU	United Kingdom
760b			Testing TPB constructs of INT, ATT, PBC, and SN on predicting public transit use	PT	United Kingdom
762a	Noblet et al.	2014	Investigating predictors of car use reduction	CU	USA
762b			Investigating predictors of prioritizing bicycle v car use	BK	USA
762c			Investigating predictors of using public transport	PT	USA
764	Onwezen et al.	2013	Testing integration of TPB with norm-activation model on predicting environmentally friendly traveling behavior	GC	Netherlands
767	Verplanken et al.	1998	Field experiment testing strength of habit construct on TPB by asking respondents to think about circumstances of BEH	GC	Netherlands
801a	Bamberg	2006	Testing use of public transit before a significant move	PT	Germany
801b			Testing use of public transit after a significant move	PT	Germany
802	Jou et al.	2011	Examining willingness of motorcycle riders to stop engine while stopped at red lights instead of idling engine	GC	Taiwan
806a	Zailani et al.	2016	Antecedents of INT to use public transit to commute to work	PT	Malaysia
806b			Antecedents of INT to use public transit to commute to shopping	PT	Malaysia
806c			Antecedents of INT to use public transit to commute to leisure areas	PT	Malaysia
808a	Donald et al.	2014	Efficacy of TPB at predicting pro environmental BEH (car use behavior, inverted)	CU	UK
808b			Efficacy of TPB at predicting pro-environmental BEH (use of PT)	PT	UK
809	Kaewkluengklom et al.	2017	TPB predictions of pro environmental BEH in Thailand (car use reduction)	CU	Thailand
901	Ru et al.	2019	Antecedents of INT to reduce particulate emissions (PM2.5) caused by transport	GC	China
903	Cai et al.	2019	Measuring interactions of TPB constructs towards a bicycle sharing program	BK	China
906a	Ru et al.	2018	Interaction effects of experiential ATT and descriptive SN upon green travel INT	GC	China
906b			Interaction effects of experiential ATT and injunctive SN upon green travel INT	GC	China
906c			Interaction effects of instrumental ATT and descriptive SN upon green travel INT	GC	China
906d			Interaction effects of instrumental ATT and injunctive SN upon green travel INT	GC	China
908	Shi et al.	2017	Antecedents of INT towards using public transportation	PT	China
919	Fu and Juan	2017	Applying TPB model towards predicting public transit usage	PT	China
931a	Bachmann et al.	2018	Applying TPB model towards predicting carpooling behavior (passenger sub-sample)	CU	Switzerland
931b			Applying TPB model towards predicting carpooling behavior (driver sub-sample)	CU	Switzerland

937a	Hoang-Tung et al.	2017	Interactions of ATT, PBC, INT upon past public transit (bus) usage for work	PT	Japan
937b			Interactions of ATT, PBC, INT upon past public transit (bus) usage for shopping	PT	Japan
937c			Interactions of ATT, PBC, INT upon past public transit (bus) usage for dinner	PT	Japan
947a	Carrus et al.	2008	Applies TPB model towards explaining past public transit BEH	PT	Italy
949a	Wolf and Seebauer	2014	Interactions of ATT, PBC, and SN towards e-bike use for work BEH	BK	Austria
949b			Interactions of ATT, PBC, and SN towards e-bike use for shopping BEH	BK	Austria
949c			Interactions of ATT, PBC, and SN towards e-bike use for leisure BEH	BK	Austria
950	Herrenkind et al.	2019	Antecedents of INT (ATT, PBC, SN) to use public transit	PT	Germany
952	Chen and Chao	2011	Antecedents of INT (ATT, PBC, SN) to switch travel modes to public transit	PT	Taiwan
953a	Frater et al.	2017	Antecedents of INT (ATT, PBC, SN from friends) towards adolescents' bicycle use	BK	New Zealand
953b			Antecedents of INT (ATT, PBC, SN from parents) towards adolescents' bicycle use	BK	New Zealand
955	Morten et al.	2018	Applies full TPB model towards explaining past BEH (avoiding air travel)	GC	United Kingdom
956	Paris et al.	2008	Intercorrelations of antecedents of BEH (reducing speeding / environmental reasons)	GC	Belgium

*$n_{studies}$ = 40
**$n_{matrices}$ = 63
***PT = public transport, GC = green commuting, CU = reduce car use, WL = walk, BK = bicycle, ED = eco-driving

Table 1: Summary of 40 Studies Selected for This Study.

Data analysis:

Correlations between constructs are inputs for a MASEM model. There are disagreements for correcting the correlations with measures of internal consistency or reliability. Schmidt and Hunter (2015) are in favor of correcting the correlations for attenuation. However, Rosenthal (1991) argues against correcting the correlations. In fact, there exist two major issues for correcting the correlations: first, corrected coefficients can exceed one; second, not all studies publish the reliability measure or Cronbach's alpha. In addition, Cheung (2015b: 244) points out problems for correcting correlations in relation to MASEM. Accordingly, the correlations for this study are used without correction or other treatment such as Fisher's z transformation.

There are two modeling approaches available for MASEM: both fixed-effect and random effect models. A fixed-effects model assumes that studies being analyzed share one population mean. Accordingly, the homogeneity of data is critical. The interpretation of findings from the fixed-effects model is assumed to be limited to the studies being analyzed (Cheung, 2015b: 224). By contrast, a random effects model allows for variation of population parameters between studies. As a result, the findings of the random effects model are more realistic. In this study, both models are tried and, as recommended by Cheung (2015a and b), one will be chosen for interpretation based on goodness-of-fit indices. The null hypothesis H_0, the assumption of homogeneity of data between studies, will be tested and the results will determine the use of a fixed- or random-effects model.

Summary effects for correlation:

The 63 correlation matrices collected from 40 studies on ecofriendly behavior in transportation are summarized in Table 2.

ID	Sample Size (N)	BEH-INT	BEH-ATT	BEH-PBC	BEH-SN	INT-ATT	INT-PBC	INT-SN	ATT-PBC	ATT-SN	PBC-SN
315a[+]	250	0.245	0.10	0.173	0.173	0.529	0.424	0.316	0.480	0.332	0.173
327	1335	0.819	0.705	0.621	0.733	0.779	0.675	0.768	0.667	0.746	0.721
360	890	0.47	0.60	0.55	0.29	0.73	0.64	0.44	0.72	0.54	0.37
366	190	0.76	0.46	0.30	0.22	0.56	0.35	0.41	0.16	0.17	0.43
398	239	0.30	0.52	0.69	0.06	0.30	0.32	0.13	0.45	0.15	0.02
412c	198	0.60	0.48	0.59	0.24	0.54	0.68	0.34	0.51	0.21	0.26
501a	517	0.75	0.55	0.69	0.43	0.76	0.91	0.61	0.69	0.61	0.69
501b	437	0.48	0.12	0.17	0.03	0.50	0.25	0.35	0.10	0.53	0.12
707	175	0.79	0.42	0.64	0.48	0.52	0.66	0.56	0.41	0.54	0.38
720a	68	NA	NA	NA	NA	0.58	0.44	0.26	0.04	0.34	-0.10
720b	150	NA	NA	NA	NA	0.36	0.38	0.32	-0.06	0.28	0.26
734	186	0.715	0.388	0.602	0.538	0.446	0.756	0.704	0.542	0.524	0.677
741b	1810	0.426	0.293	-0.495	-0.187	0.54	-0.14	0.505	-0.085	0.254	0.155
743	578	0.695	0.470	0.436	0.432	0.676	0.610	0.630	0.596	0.551	0.529
745a	620	NA	NA	NA	NA	0.38	0.59	0.60	0.32	0.42	0.51
745b	620	NA	NA	NA	NA	0.49	0.60	0.32	0.48	0.30	0.42

745c	620	NA	NA	NA	NA	0.49	0.60	0.39	0.60	0.50	0.62
748a	1275	0.301	0.175	0.412	0.135	0.115	0.250	0.306	0.130	0.021	0.145
748b	1275	0.301	0.140	0.412	0.135	0.235	0.250	0.306	0.160	0.138	0.145
748c	1275	0.301	0.310	0.412	0.135	0.175	0.250	0.306	0.229	0.080	0.145
750	300	NA	NA	NA	NA	0.59	0.49	0.48	0.51	0.64	0.40
757a	452	0.95	0.508	0.42	0.36	0.537	0.44	0.38	0.281	0.264	0.17
757b	452	0.94	0.705	0.50	0.48	0.751	0.53	0.51	0.438	0.485	0.51
758	595	NA	NA	NA	NA	0.24	0.22	0.19	0.19	0.30	0.09
760a	229	0.88	0.51	0.40	0.36	0.55	0.35	0.46	0.27	0.39	0.11
760b	229	0.86	0.39	0.26	0.33	0.43	0.25	0.24	0.26	0.32	0.22
762a	1340	0.11	0.10	0.03	0.13	0.47	0.15	0.30	0.15	0.52	0.09
762b	1340	0.08	0.08	0.26	0.06	0.47	0.15	0.30	0.15	0.52	0.09
762c	1340	0.04	0.13	0.13	0.07	0.47	0.15	0.30	0.15	0.52	0.09
764	617	0.306	0.254	0.162	0.14	0.431	0.557	0.391	0.341	0.248	0.282
767	200	0.20	0.11	0.15	0.03	0.48	0.15	0.35	0.30	0.39	0.08
801a	169	0.77	0.72	0.72	0.63	0.83	0.80	0.79	0.89	0.87	0.78
801b	169	0.82	0.69	0.71	0.63	0.88	0.84	0.80	0.82	0.88	0.78
802	545	0.51	0.25	-0.10	-0.48	0.35	-0.12	-0.69	-0.08	0.31	0.06
806a	392	NA	NA	NA	NA	0.668	0.597	0.352	0.634	0.45	0.575
806b	392	NA	NA	NA	NA	0.595	0.292	0.247	0.457	0.202	0.29
806c	392	NA	NA	NA	NA	0.536	0.491	0.461	0.534	0.756	0.555
808a	827	0.87	0.37	0.4	0.3	0.41	0.41	0.38	0.36	0.31	0.38
808b	827	0.8	0.42	0.5	0.28	0.45	0.59	0.37	0.46	0.27	0.35
809	600	0.19	0.16	0.17	0.08	0.47	0.671	0.71	0.41	0.4	0.62
901	425	NA	NA	NA	NA	0.54	0.66	0.52	0.41	0.37	0.37
903	395	0.675	0.55	0.609	0.63	0.672	0.718	0.623	0.722	0.679	0.667
906a	419	NA	NA	NA	NA	0.534	0.466	0.247	0.26	0.284	0.039
906b	419	NA	NA	NA	NA	0.534	0.466	0.335	0.26	0.467	0.176
906c	419	NA	NA	NA	NA	0.4	0.466	0.247	0.206	0.406	0.039
906d	419	NA	NA	NA	NA	0.4	0.466	0.335	0.206	0.232	0.176
908	595	NA	NA	NA	NA	0.64	0.51	0.48	0.5	0.53	0.32
919[+]	6602	0.762	0.663	0.141	0.625	0.735	0.2	0.755	0	0.735	0.141
931a	181	0.07	0	0.12	0	0.46	0.51	0.54	0.33	0.25	0.33
931b	161	0.28	0.2	0.22	0.19	0.38	0.59	0.61	0.4	0.27	0.32
937a	225	0.322	0.124	0.122	NA	0.383	0.239	NA	0.333	NA	NA
937b	259	0.33	0.253	0.136	NA	0.508	0.164	NA	0.333	NA	NA
937c	248	0.363	0.191	0.245	NA	0.38	0.193	NA	0.333	NA	NA
947a	180	0.76	0.16	0.58	0.55	0.26	0.5	0.5	0.24	0.27	0.42
949a	472	NA	0.44	0.13	0.09	NA	NA	NA	0.37	0.29	0.14
949b	1070	NA	0.36	0.14	0.17	NA	NA	NA	0.37	0.29	0.14
949c	1109	NA	0.22	0.15	0.13	NA	NA	NA	0.37	0.29	0.14
950	180	NA	NA	NA	NA	0.67	0.49	0.47	0.52	0.47	0.24
952	442	NA	NA	NA	NA	0.46	0.25	0.43	0.29	0.36	0.16
953a	331	NA	NA	NA	NA	0.58	0.27	0.68	0.28	0.57	0.26
953b	331	NA	NA	NA	NA	0.58	0.27	0.64	0.28	0.47	0.38
955	194	0.43	0.34	0.14	0.29	0.71	0.2	0.56	0.23	0.46	0.07
956*	116	NA	0.208	0.412	0.115	0.084	0.5	0.191	0.293	-0.042	0.252
N (correlations)		*39*	*43*	*43*	*40*	*60*	*60*	*57*	*63*	*60*	*60*

Notes. Studies with multiple samples or different research are indicated alphabetically i.e. a, b, c
BEH = pro-environmental behavior, INT = behavioral intention, ATT = attitude, PBC = perceived behavioral control, SN = subjective norm
[+]correlations presented as squares; these values represent square roots
*matrix of study 956 excluded from fixed-effects model due to not being positive-definite

Table 2: Raw Correlations from the Sample.

There exist some studies with multiple matrices depending on types of behaviors on the choices of transportation methods such as driving a car, using public transportation (bus, subway, etc.), carpooling, walking, and riding a bicycle. For a precautionary measure, the matrices were checked for positive definiteness as recommended by Cheung (2015b: 267). Non-positive definite matrices preclude the use of a fixed effect MASEM model due to computational error. The test for non-positive definite matrices (Cheung, 2015a) revealed one matrix was not positive definite and was excluded for the first stage analysis for the fixed effects model. Accordingly, 62 matrices are used for trying the fixed effects model. The presence of non-positive definite matrices does not create a problem for the random effects model. Accordingly, the non-positive definite matrix is added back in when fitting the random effects model.

Analysis with MASEM:

This study uses meta-analytic structural equations modeling (MASEM) for fitting data to the TPB. Three different models are tested using the two-stage structural equation modeling (TSSEM) approach (Cheung 2015a and b), which is available as a package for R (R Core Development Team, 2019). In the first stage, TSSEM pools correlation matrices. At the second stage, the program performs SEM analysis and estimates parameters along with goodness-of-fit indices. At the second stage, researchers should provide two to three matrices depending on model specification. An A (asymmetric) matrix is necessary to show paths in an SEM model. An S (symmetric) matrix represents the variance and/or covariance of variables in the model. An F matrix is used for identifying measurement variables from second- or higher-order variables. Because three models in this study lack second- or higher-order constructs, A and S matrices are prepared for the second stage analysis. Figure 3 shows the elements of the A and S matrices for Model 2, Ajzen's original TPB model.

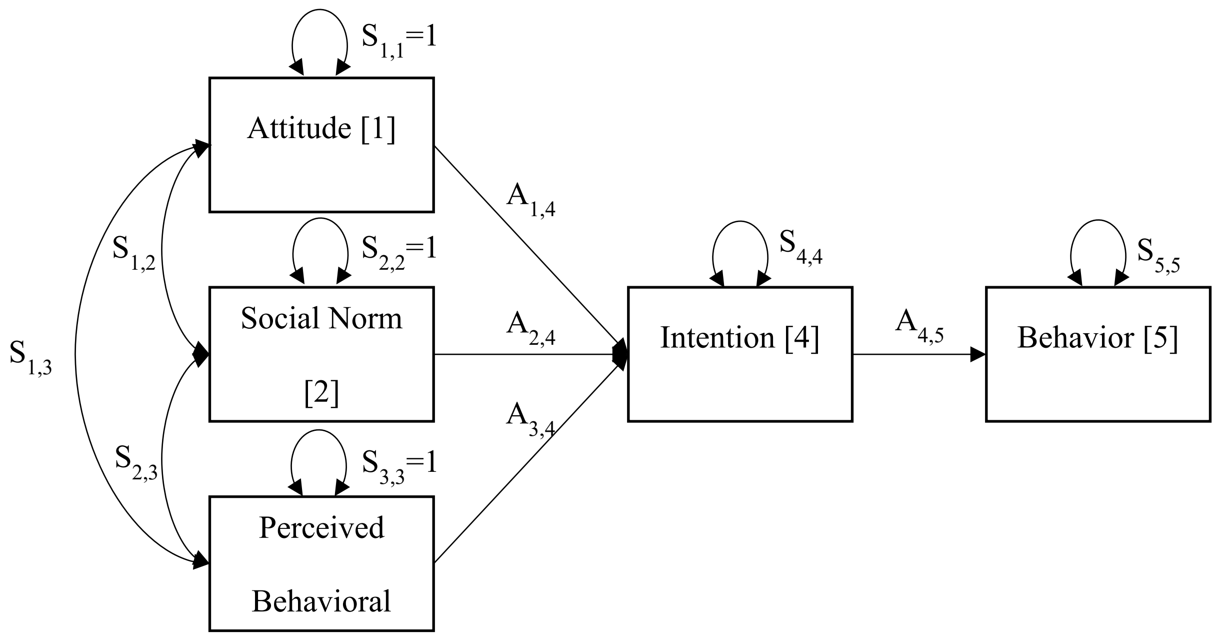


Figure 3: Elements of the A and S Matrices for Model 2.

Based on Figure 3, the A and S matrices can be created as follows:

$$\mathbf{A} = \begin{bmatrix} 0 & 0 & 0 & A_{1,4} & 0 \\ 0 & 0 & 0 & A_{2,4} & 0 \\ 0 & 0 & 0 & A_{3,4} & 0 \\ 0 & 0 & 0 & 0 & A_{4,5} \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix} \text{ and } \mathbf{S} = \begin{bmatrix} 1 & S_{1,2} & S_{1,3} & 0 & 0 \\ S_{2,1} & 1 & S_{2,3} & 0 & 0 \\ S_{3,1} & S_{3,2} & 1 & 0 & 0 \\ 0 & 0 & 0 & S_{4,4} & 0 \\ 0 & 0 & 0 & 0 & S_{5,5} \end{bmatrix}.$$

Figure 4: A and S matrices for TSSEM

Since the S matrix is symmetric, the upper half can be ignored. TSSEM allows users to specify a type of the matrix such as full, symmetric (for the bottom half) or diagonal.

For interpreting estimates, this study adopts Cohen (1992)'s recommendation: *r* = 0.10 for weak correlation, *r* = 0.30 for moderate correlation, and *r* = 0.50 for strong correlation. However, this recommendation is intended as a rule of thumb rather than as a solid guideline. RMSEA and SRMR along with a χ^2 statistic will be used for assessing the goodness-of-fit of the models. Cheung (2015b: 233) recommends the use of RMSEA and SRMR over CFI and TLI for the results by TSSEM, which utilizes a weighted-least square (WLS) algorithm. He calls for additional studies on the use of goodness-of-fit indices for MASEM studies, which employ WLS computational methods.

Results:

There are two options to run a MASEM model, depending on sample assumptions. A fixed-effects model is appropriate if the sample is homogenous or comes from the same population. If, instead, the samples are heterogeneous, a random effects model is appropriate. In TSSEM analysis, the first-stage analysis involves pooling correlation matrices and conducting confirmatory factor analysis. The test statistics for checking the homogeneity of the sample include χ^2 and its significance, RMSEA, and SRMR (Cheung, 2015b: 247). The null hypothesis of the first-stage data analysis, H_0, is the assumption of homogeneity of data. This study tries a fixed-effects model at the first stage with TSSEM for testing the homogeneity of the sample. The goodness-of-fit indices for the fixed-effects model are χ^2 (degree of freedom = 506 and sample size = 39,191) = 19739.0765 with $p < 0.001$, RMSEA = 0.2452, and SRMR = 0.2159. This model is ill-fitted. Thus, the null hypothesis of a homogeneous sample is rejected. The heterogeneity of the sample calls for analysis using random-effects models. Three random-effect models, along with pertinent goodness-of-fit indices, are presented and discussed.

Model 1:

Model 1 is similar to the original TPB model except that it excludes the correlations between independent constructs, which have been dropped to test the efficacy of parsimonious modeling. Figure 5 presents the estimated path coefficients of Model 1.

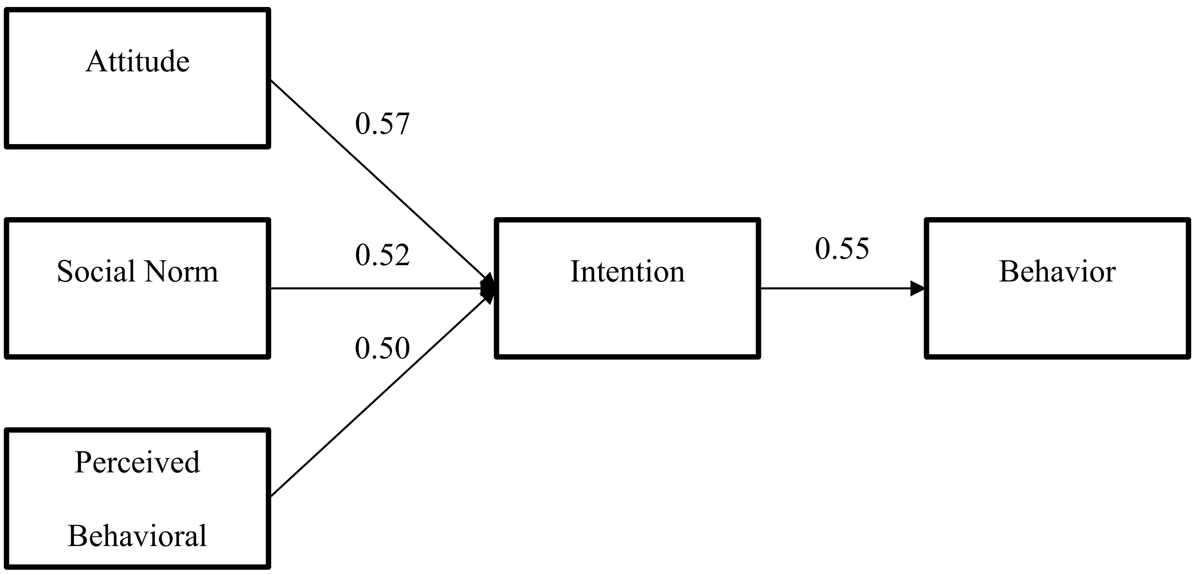


Figure 5: Model 1 Results without Correlations between Independent Constructs.

Goodness-of-fit indices for Model 1 are χ^2 (degree of freedom = 6 and sample size = 39,307) = 65.2521 with $p < 0.001$, RMSEA = 0.0159, and SRMR = 0.0643. The values of RMSEA and SRMR are acceptable or within their respective threshold. However, the p-value for χ^2 is significant or smaller than 0.001, which should be greater than or equal to 0.05. The path coefficients between Attitude and Intention, Perceived Behavioral Control and Intention, Subjective Norm and Intention, and Intention and Behavior are all greater than 0.50, indicating strong relationships.

Model 2:

Model 2 represents the original TPB model, meaning that it retains the correlations between the independent constructs ATT, PBC, and SN. Figure 6 exhibits the parameter estimates of the original TPB model.

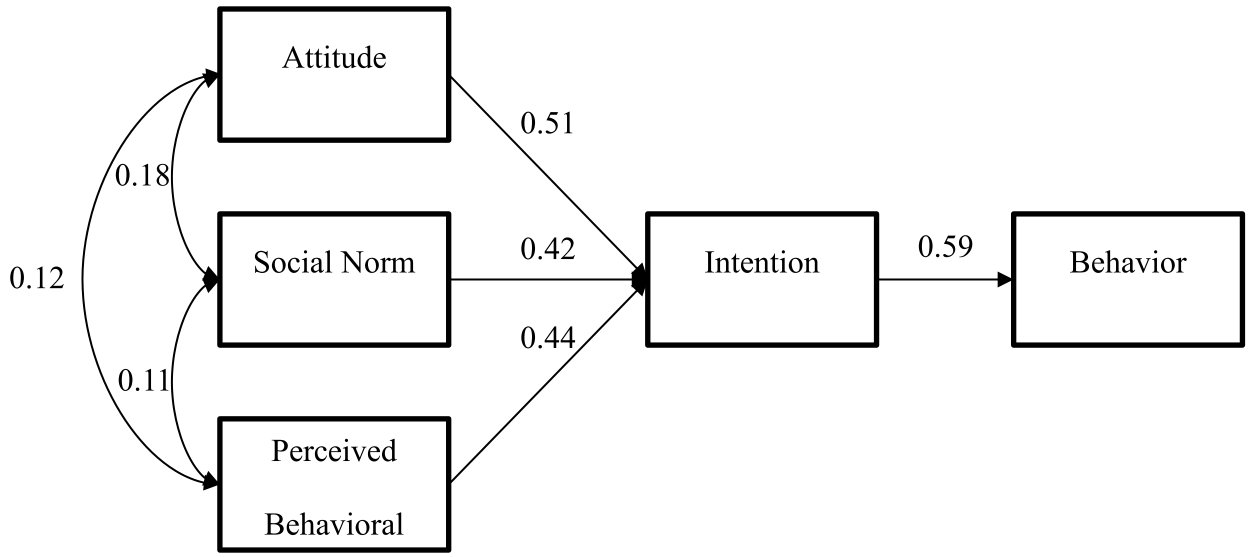


Figure 6: Model 2 Results with Original TPB Model.

Goodness-of-fit indices for the result of Model 2 are χ^2 (degree of freedom = 3 and sample size = 39,307) = 8.7642 with p = 0.0326, RMSEA = 0.0070, and SRMR = 0.0338. All indices are significantly improved from those of Model 1, although the p-value of the χ^2 index still falls below the recommended threshold of 0.05 or greater. The relationship between Intention and Behavior, at 0.59, is strongest among the estimates. The relationship between Attitude and Intention, 0.51, is strong. The remaining path coefficients show moderate strength.

Model 3:

Model 3 represents the extended TPB model by including a direct relationship between Perceived Behavioral Control and Behavior. Figure 7 displays estimated path coefficients for Model 3.

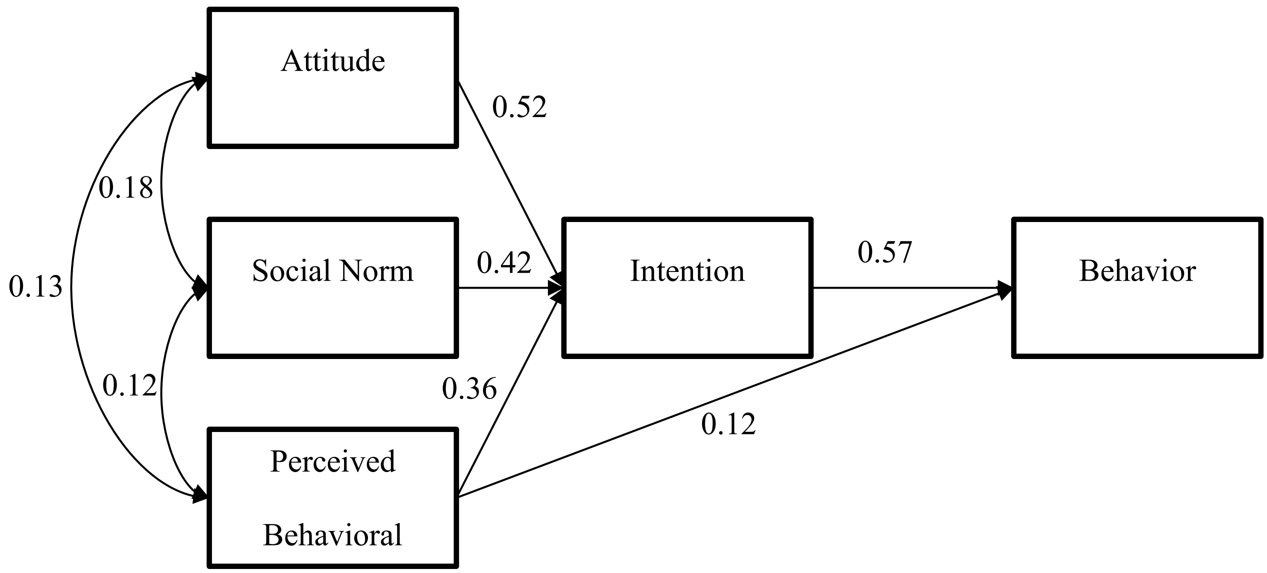


Figure 7: Model 3 Results with Extended TPB Model

Goodness-of-fit indices for the result of Model 2 are χ^2 (degree of freedom = 2 and sample size = 39307) = 5.1565 with p = 0.0759, RMSEA = 0.0063, and SRMR = 0.0238. All goodness-of-fit indices are acceptable and noticeably improved from those of Model 2. However, the direct relationship between PBC-BEH is both weak (relationship strength of 0.12) and inconclusive (the 95% confidence interval spans 0 into negative values). Therefore, we cannot draw conclusions from this relationship.

Judging the models by GFIs alone, Model 3 is the best fit; however, Model 2 is stronger from a parsimonious standpoint and has significance on all paths. Therefore, we make our recommendation based on the specificity of the behavior being studied. Kaiser and Gutscher (2003) indicate that the strength of the PBC-BEH link is determined by the specificity of BEH. Given these findings, the authors of this study recommend using Model 3 when studying specific behaviors and Model 2 when studying a variety of behaviors.

Discussion and Conclusion:

We examined three models for ecofriendly behavior on personal transportation using MASEM that utilized TSSEM. Goodness-of-fit indices were used for evaluating the models. The authors recommend the use of Model 2 when behaviors are nonspecific, and Model 3 when behaviors are specific. Table 3 shows the three models' indices along with the recommended threshold values.

Goodness-of-fit Indices	Recommended Threshold	Model 1	Model 2	Model 3
χ^2 of Target Model		65.2522	8.7643	5.1565
p-value of Target Model	≥ 0.05	0.0000	0.0326	0.0759
RMSEA	≤ 0.08	0.0159	0.0070	0.0063
SRMR	≤ 0.08	0.0643	0.0338	0.0238
TLI	≥ 0.95	0.9499	0.9903	0.9920
CFI	≥ 0.90	0.9700	0.9971	0.9984
AIC		53.2522	2.7643	1.1565

Table 3: Comparison of Goodness-of-fit Indices.

Pro-environmental transportation behavior is primarily driven by intent, which in turn is driven primarily by attitudes. This is not a surprising finding given the support for the intention-behavior relationship within TPB literature. However, what was more curious was the relationship between PBC and BEH. While including this link (Model 3) led to a stronger model in terms of GFIs, the relationship strength was weak, and the 95% CI included 0 indicating non-significance.

Model 3 was the best by every aspect of the GFIs. In particular, AIC (Akaike Information Criterion) indicated that Model 3 was the best fit for explaining ecofriendly transportation behavior. The relationship between INT and BEH is strong, which supports the TPB literature's assertions that fostering individuals' intentions towards using eco-friendly modes of transportation is critical to their actual real-world use. In addition, these findings indicate that people's attitude toward eco-friendly transportation strongly influences their behavioral intention. As mentioned previously, the direct relationship between Perceived Behavioral Control and Behavior is weak and inconclusive, as the 95 percent confidence interval for this relationship includes zero (0) as shown in Table 4.

Path	Model 1			Model 2			Model 3		
	Estimate	Lower Bound	Upper Bound	Estimate	Lower Bound	Upper Bound	Estimate	Lower Bound	Upper Bound
Attitude → Intention	0.571	0.539	0.604	0.514	0.477	0.551	0.516	0.479	0.553
Subjective Norm → Intention	0.518	0.478	0.559	0.422	0.372	0.473	0.425	0.374	0.476
Perceived Behavioral Control → Intention	0.503	0.463	0.543	0.444	0.395	0.493	0.357	0.258	0.458
Perceived Behavioral Control → Behavior	NA	NA	NA	NA	NA	NA	0.118	-0.004	0.233
Intention → Behavior	0.554	0.499	0.610	0.593	0.534	0.654	0.573	0.510	0.637
Correlation: ATT ↔ SN	NA	NA	NA	0.181	0.127	0.235	0.179	0.124	0.233
Correlation: SN ↔ PBC	NA	NA	NA	0.110	0.052	0.168	0.117	0.059	0.176
Correlation: ATT ↔ PBC	NA	NA	NA	0.123	0.067	0.178	0.132	0.075	0.188

Table 4: Summary Results from MASEM models.

Although Model 3 shows the best fit among three models, the direct relationship between Perceived Behavioral Control and Behavior is inconclusive at best. This supports the findings of the study on Swiss residents by Kaiser and Gutscher (2003), which indicates that PBC is only a strong direct predictor of BEH in specific contexts. As an antecedent to generalized pro-environmental BEH, PBC's predictive power reduces to non-significant levels. The specificity of the behaviors studied in this MASEM falls between that of Kaiser and Gutscher (2003)'s two boundaries; it is more specific than "generalized pro-environmental BEH" but more general than Kaiser and Gutscher's more specific "reduce car use" and "recycle glass" behaviors. A path coefficient of 0.12 is comparable to the 0.11 which Klöckner (2013) found when synthesizing a larger spectrum of behaviors. This all seems to indicate that the predictive ability of PBC upon

BEH drops off sharply as the types of behavior comprising the BEH construct become more varied. This finding calls for additional studies for this relationship.

The 95 percent confidence intervals for the remaining estimates indicate that their relationships are statistically significant. The MASEM approach supports existing theory. Links between constructs in the model (e.g. INT-BEH and ATT-INT) are from moderate to strong ranging from 0.36 at their lowest (PBC-INT) to 0.57 (INT-BEH) at their strongest. Correlations between ATT and SN and PBC and ATT are weak. The major contribution of this study is testing and demonstration of a novel method of performing SEM in the transportation area. The MASEM method has been tested before in the context of generalized pro-environmental behavior (Bamberg and Möser, 2007) but to the authors' knowledge has not been applied to the TPB in the context of eco-friendly transportation. Another major finding is support for the TPB's main thesis that INT is the most critical predictor of BEH. In addition, a useful finding is support for the scalability of the direct PBC-BEH relationship as a function of the specificity of the BEH studied (i.e. the more specific the BEH, the stronger the direct PBC-BEH predictive capability is liable to be). The major limitation of this study resides within that of primary studies included in analysis, which mostly measure self-reported attitudes and perception instead of actual behavior. Thus, the authors of this study suggest future studies focus more on linking TPB constructs with measures of actual behavior.

Paper 2: Antecedents of Eco-Friendly Driving Intentions and Behavior

Introduction:

Americans consume 9.3 million barrels of gasoline per day for driving (EIA.gov). This amount, which is used in large part for personal transportation, as industrial and commercial transportation is fueled by kerosene-derived products such as diesel and jet fuel, accounts for nearly half of all US petroleum consumption (EIA.gov). Motor vehicles are responsible for carbon emissions that are linked to local environmental effects such as acid rain in addition to large-scale environmental effects such as anthropogenic climate change (Schauer, Kleeman, Cass, & Simoneit, 2002; Zacharof et al., 2016). Motor vehicle efficiency has been on the rise for many years, especially since the advent of hybrid and battery-electric vehicles (Ehsani, Gao, Longo, & Ebrahimi, 2018). However, such eco-friendly vehicles constitute a small percentage of the total market in the United States. The remaining personal vehicles in the US have conventional drivetrains with either negligible or zero ability to recapture energy from braking.

In addition to eco-friendly vehicles, a driver's habits and behaviors are considered as an important factor that affects fuel-efficiency and emission issues for both commercial and personal motor vehicle operators. Few studies have addressed the human element of transportation-caused negative externalities (e.g., particulate pollution, CO_2, greenhouse emissions, and petrochemical consumption). Although there are studies on pro-environmental behaviors, they mostly focus on different actions such as recycling and reuse (e.g., Collado, Staats, & Sancho, 2019; De Leeuw, Valois, Ajzen, & Schmidt, 2015). To address fuel efficiency, we assembled a holistic model of fuel-efficient behavior and its antecedents. The domain of pro-environmental behavior provides a framework with which to measure behavioral impacts upon, and hopefully leading to, increased fuel efficiencies and reduced emissions. We chose Theory of Planned Behavior or TPB (Ajzen, 1991) for our research framework, which demonstrates good predictive and explanatory power in the realm of antecedents and their behavioral consequences. We propose two research questions: (1) What are the relationships between and/or among the antecedents of eco-friendly driving intentions and self-reported driving behaviors? (2) Will our findings confirm the TPB model? To answer these questions, we develop a series of hypotheses and test them using data collected three sources. The major purpose of our study is finding relationships between antecedents of eco-friendly driving intentions and behavioral consequences.

Eco-Driving:

Sivak and Schoettle (2012) defined eco-driving as "those strategic decisions (vehicle selection and maintenance), tactical decisions (route selection and vehicle load), and operational decisions (driver behavior) that improve fuel economy." In an increasingly motorized world, traffic congestion increases within cities alongside deleterious effects of combustion-engine emissions. Promoting more eco-friendly driving behaviors leads to improvements in environmental quality, can reduce fuel consumption, and through reducing aggressiveness while driving, can save on maintenance costs (Saboohi & Farzaneh, 2008). Much of the existing eco-driving literature focuses on vehicles with manual transmissions, which account for the majority of light duty vehicles in Europe; in the USA, less than ten percent of light duty passenger vehicles are equipped with a manual transmission (Richardson, 2018; Weinberger, Jörissen, & Schippl, 2012).

Regardless of transmission choice, however, the one of the largest behavioral contributors to fuel consumption is driving style (Nader, 1991; Sanguinetti, Kurani, & Davies, 2017; Wåhlberg, 2007)

It should be noted that the behaviors surrounding eco-driving do not interfere with safety. Eco-driving is not the same as hypermiling. “Hypermiling,” as defined by Barkenbus (2010), involves sacrificing safety for fuel efficiency. Hypermiling stands as a severe contrast to the definition of eco-driving by Sivak and Schoettle (2012). Compromising safety is an undesirable result of prioritizing the goal or saving fuel over all other factors. Goal theory holds that humans, when presented with and incentivized by goals, risk developing “tunnel vision” and focusing on those goals to the exclusion of other factors (Locke & Latham, 2006). We mention goal theory mostly due to its relationship with a common criticism of eco-driving – unsafe driving behaviors. Considering multiple behavioral factors such as goals and motives, which could impact fuel efficiency, Dogan, Bolderdijk, and Steg (2014) analyzed priority hierarchy as it pertains to eco-driving. They found that introducing a goal of economical driving was enough to make eco-driving a priority, but that this goal was placed below safety and time pressure. Similarly, Andrieu and Pierre (2012) also demonstrated that eco-driving encouragement did not have to be intrusive or sacrifice safety.

Estimates indicate that eco-driving behaviors, many as simple as accelerating more gently, could lead to fuel savings between 10% and 20% (Barkenbus, 2009; Tyler, 2013). Johansson, Gustafsson, Henke, and Rosengren (2003) indicated that effecting a significant change upon CO2 emissions required motivation as well as training. However, smaller changes could be induced with non-intrusive, gentle encouragement. Feedback was commonly found to help encourage eco-driving efforts. Ando and Nishihori (2012) found that the most relevant factors playing into eco-driving success was the frequency of feedback provided, the frequency of the user in checking the feedback system, and operation factors like average speed and distance. Barkenbus (2010) noted that the "gamified" display readouts on hybrids such as the Toyota Prius were some of the most effective means for encouraging eco-driving.

Beyond feedback, Beusen et al. (2009) evaluated the impact of eco-driving training for 10 drivers over a period of 10 months. Difficulty with data collection made drawing sound conclusions difficult, but the study did highlight some aspects of eco-driving. Relevant desirable behaviors included maintaining steady speeds, anticipating traffic flow, smooth deceleration, and driving slower than 80mph on freeways. The main takeaway was that it was difficult to apply a "one size fits all" approach to eco-driving training. Even with a sample size as small as 10, each subject displayed a very different learning style and skill retention rate in the months following the course. It implied that, in addition to training, some form of feedback should be used to normalize the variance in driver behavior.

Although it could be argued that driving behavior is largely autonomous, and influenced chiefly by past behavior, Bamberg, Ajzen, and Schmidt (2003) insisted that such factors did not overwhelm reasoned action. The authors studied choice of travel method among students at the University of Giessen in Germany, before and after the introduction of a bus ticket designed as an intervention to encourage pro-environmental behavior. Using the TPB as a framework, the study found that even in heavily habit- and past behavior-based actions, such as taking the bus versus driving, behavior could be disrupted by presenting an attractive option such as a prepaid bus ticket. As they concluded, human social behavior was at least partially regulated by conscious processes, even if almost entirely autonomous otherwise. Relevant minor events – such as the prepaid bus ticket – could serve to disrupt largely-autonomous behaviors and prompt reasoned action.

Theory of Planned Behavior and Eco-Driving:

The Theory of Planned Behavior (TPB) provides a well-established theoretical and empirical framework for understanding eco-driving and other pro-environmental behavior (Ajzen, 1988, 1991). According to TPB, intentions are the immediate antecedent to behavior. TPB was originally proposed by Ajzen (1985) as an offshoot from the Theory of Reasoned Action and codified in 1991 (Ajzen, 1991). While intention is the primary antecedent to behavior, TPB identifies three core motivational components that serve as antecedents to intention: the individual's attitude towards performing the behavior; the individual's perception of the normative environment within which they exist; and the individual's perception of their level of control over their behavior. This relationship among the constructs is shown in Figure 8.

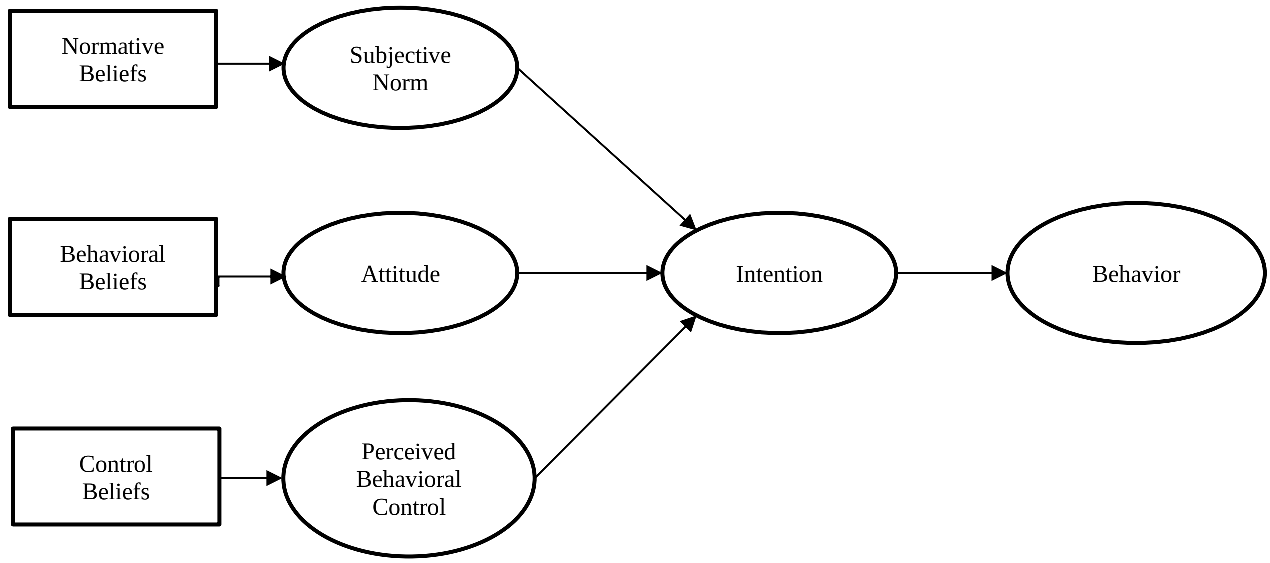


Figure 8: Theory of Planned Behavior (Ajzen, 1991)

Based on the core TPB in Figure 8 and relevant literature, we propose three models with eco-driving as the dependent variable. The three models differ for dealing with Intention: as an independent variable in Model 1 and as a mediator in Models 2 and 3. In Model 1 intention, subjective norms, attitudes, and perceived behavioral control variables are all hypothesized to have a direct relationship with eco-driving behavior. Model 2 would be described as a partially mediated model in the Baron and Kenny (1986) framework, with subjective norms, attitudes, and perceived behavioral control variables believed to both directly and indirectly impact eco-driving behavior through intentions. Model 3, which directly resembles the TPB model in Figure 8, would be the full mediation model in the Baron and Kenny (1986) framework with only intention directly impacting eco-driving behavior and the remaining variables working indirectly through intention.

The proposed relationships in Models 1 through 3 are codified in the following hypotheses:

H1: Driver’s perceptions of subjective norms, attitudes about eco-driving, perceived behavioral control for saving fuel, self-efficacy for eco-driving, and intentions to drive fuel efficiently will be positively related to eco-driving behavior.

H2a: Driver’s perceptions of subjective norms, attitudes, perceived behavioral control, and self-efficacy will be positively related to intentions to drive fuel efficiently.

H2b: Driver’s perceptions of subjective norms, attitudes, perceived behavioral control, and self-efficacy will be indirectly related to eco-driving behavior through intentions to drive fuel efficiently.

H3: The relationship between driver’s perceptions of subjective norms, attitudes, perceived behavioral control, and self-efficacy and eco-driving behavior will be fully mediated through intentions to drive fuel efficiently.

Methodology

Participants and Procedure:

Participants from three sources were recruited to complete a Qualtrics online survey to provide a diverse set of backgrounds: reddit automotive forums ($N = 62$), a psychology department participant pool ($N = 115$), and Amazon's Mechanical Turk (mTurk; $N = 241$). The mTurk population was managed through TurkPrime (Litman, Robinson, & Abberbock, 2016). Of the 418 participants who clicked on the link, 322 (77%) completed at least 85% of the survey and passed attention checks (see below). Missing data was present for 48 participants, with the number of items not answered ranging from 1 to 8. Van Buuren and Groothuis-Oudshoorn's (2011) mice package for R was used to impute missing values across five imputed data sets.

Overall 52.48% of the sample self-reported as male but there were significant gender differences between samples, χ^2 (2) = 23.70, $p < .05$: the forum sample was 78.57% male, the mTurk sample was 57.14% male, and the student sample was 38.39% male. The typical participant self-reported as white/Caucasian (65.53%) and this distribution did not differ across samples, χ^2 (2) = 2.69, $p = .26$. On average, participants were 28.68 years old ($SD = 10.92$), but ages did differ across the groups, $F(2, 305) = 96.38$, $p < .05$, with the college students ($M = 19.70$, $SD = 2.43$) being significantly younger than both the forum participants ($M = 30.90$, $SD = 12.90$, t (25.41) = 4.31, $p < .05$) or mTurk participants ($M = 34.20$, $SD = 10.20$, t (198.83) = 17.83, p < .05. Descriptive statistics for the full sample and each subgroup are presented in Table 5.

Measures:

All measures were embedded in a Qualtrics survey and the link was provided to participants online. Participants first completed the measure of eco-driving, then completed the TPB measures, and finally completed a demographics questionnaire.

		Full Sample		Reddit	SONA	mTurk
		f	%			
Gender	Male	169	52.48	22	43	104
	Female	138	46.9	4	68	66
	Unspecified	15	4.6	2	1	12
Ethnicity	White/Caucasian	211	65.53	17	80	114
	Black/African American	45	13.98	0	19	26
	Hispanic	10	3.10	3	1	6
	Asian	23	7.14	3	5	15
	Native American	3	0.93	1	0	2
	Pacific Islander	1	0.31	0	0	1
	Other/Multiple	15	4.66	2	6	7
	Unspecified	14	4.35	2	1	11
Age Mean		28.68		30.80	19.70	34.20
Age *SD*		10.92		12.90	2.43	10.20
Age Median		26.00		27.50	19.00	32.00

Note. *N* = 322.

Table 5: Sample Demographics.

Eco-Driving. Eco-driving was measured with eight items based on techniques to reduce fuel consumption and modeled off of such measures as Andrieu and Pierre (2012). Here “efficient driving behavior” includes reducing harshness of accelerator/gas pedal usage, increasing attentiveness to upcoming road conditions, and increasing attentiveness to planning a drive before setting off. Coefficient alpha for the scale was .82.

Attention Checks. Two items were used to ensure that participants were reading the survey carefully. An example item was, "As an attention check, please select Strongly Disagree". Participants who failed these attention checks were removed from analysis.

Theory of Planned Behavior Constructs. Based on previous TPB measures, scales were created to measures perceived subjective norms, attitudes towards fuel efficiency, perceived behavioral control of fuel efficiency, self-efficacy of eco-driving behaviors, and intentions for eco-driving. The final TPB items can be found in the Appendix.

Attitude towards Saving Fuel (Att 1) was initially measured with five items adapted from Ajzen (1991) and measures respondent's attitude towards saving fuel over their next dozen drives. The items ask the respondent to rate their feelings towards saving fuel on a seven-point Likert like scale between an opposing pair of descriptors e.g. bad/good, worthless/valuable, etc. Coefficient alpha for the final four item scale was .87.

Attitude towards Moderating Highway Speed (Att2) was measured with five items adapted from Ajzen (1991) and measures the respondent's attitude towards driving at the most efficient speed for most vehicles on the highway. Here, "most efficient highway speed" was defined as 55-60 miles per hour or mph (around 90-100 kilometers per hour), even if the speed limit is above 60mph as it is in many parts of the United States. Coefficient alpha for the final four item scale was .83.

Perceived Behavioral Control – Self Efficacy over Fuel Consumption (PBC-SE) was measured with 10 items adapted from Ajzen (2002), Bandura (2006), and Oliver (2010). These items measure the respondent's perceived behavioral control, specifically the respondent's perceived self-efficacy as it pertains to saving fuel. These items are broader, general questions which focus on the ease by which the respondent can drive efficiently. Coefficient alpha for the final seven item scale (see results below) was .86.

Perceived Behavioral Control – Controllability over Fuel Consumption (PBC-C) was measured with four items adapted from Ajzen (2002), and measures the respondent's perceived level of controllability over the specific outcome of driving efficiently. Controllability measures how much control the respondent ascribes to outside factors, such as routines and processes, which are not within the respondent's own sphere of influence. Coefficient alpha for the final three item scale was .86.

Subjective Norms (SN) were measured with four items adapted from Ajzen (1991) and measure the respondent's perceived subjective norm towards driving in a fuel-efficient manner. Here, "perceived subjective norm" is defined as social pressure, spoken or unspoken, felt by the respondent from peers, passengers, friends, and other drivers. The final three item scale had a coefficient alpha of .82.

Intention was measured with four items adapted from Ajzen (2002) and measure the respondent's intention towards driving in a fuel-efficient manner. Coefficient alpha was .72.

Results

Exploratory Factor Analysis:

To initially evaluate the TPB scales a series of exploratory factor analyses were conducted. Exploratory factor analyses were conducted using maximum likelihood factoring method with varimax rotation in R using the stats package (R Core Team, 2018). Analysis of the scree plot suggested seven factors, instead of the six that we expected. Examination of the loadings indicated that the intention items illustrated an odd pattern of loadings. Because TPB specifies that the other items influence intentions, intentions were removed from the analysis was repeated. With the intention items removed, the scree analysis indicated six factors; however, the sixth factor only consisted of two loadings for negatively worded attitude items. The model was thus re-specified to have five factors. Factor loadings greater than .30 from this model are presented in Table 6.

Construct	Item	F1	F2	F3	F4	F5
Attitudes Towards Saving Fuel (Att 1)	1		.81			
	2r		-.59			
	3		.89			
	4		.81			
	5r		-.48			
Attitudes Towards Moderating Highway Speed (Att 2)	1				.44	
	2				.77	
	3r				-.81	
	4r				-.62	
	5				.69	
Perceived Behavioral Control: Self-Efficacy over Fuel Consumption (PBC-SE)	1	.64				
	2	.68				
	3	.66				
	4	.66				
	5	.67				
	6	.57				
	7	.70				
	8r		-.31			.40
	9r		-.35			.44
	10r					.40
Perceived Behavioral Control: Controllability over Fuel Consumption (PBC-C)	1r					.62
	2r					.49
	3r					.43
	4	.32		.35		
Subjective Norms (SN)	1			.85		
	2			.57		
	3			.49		.32
	4			.83		
	5			.36		
	6			.44		
	7			.44		

Note. N = 322. Loadings smaller than |.30| were removed from the table.

Table 6: Exploratory Factor Analysis and Loadings.

The factor loadings in Table 6 revealed two interesting aspects of our TPB items. For one, the pattern of loadings for the attitudes towards saving fuel and moderating highway speed suggested two separate constructs. This perception of a bifurcated attitudes is supported by Ajzen (1991), in which it is common practice to use two separate sets of items to represent attitudes towards the behavior in question. In addition, the last three items in the self-efficacy construct loaded on the same factor as the controllability construct (with two of them also loading on one of the attitude factors). All three self-efficacy items referred to the perceived value of managing fuel efficiency while driving while the controllability items focused on driver's ability to control fuel performance in their vehicle.

Results from Table 6 were used to remove items with poor factor loadings from subsequent analyses. The initial goal was to keep items with factor loadings greater than 0.70, but this restriction was relaxed to 0.50 to ensure that each scale had at least three items. Retained items are presented in black and removed items are presented in grey in Table 2.

Confirmatory Factor Analysis:

Confirmatory factor analysis with maximum likelihood estimation was conducted in R using the lavaan package (Rosseel, 2012). To evaluate model fit we examined the SRMR, RMSEA, and the CFI fit indices. Both the SRMR and the RMSEA are absolute models of fit, with values of zero indicating that the observed covariance matrix is identical to the implied covariance matrix; CFI is a measure of comparative fit where the fit of the specified model is compared to the fit of a null model. Consistent with the recommendations of Hu and Bentler (1999), SRMR values less than or equal to .08, RMSEA values less than or equal to .06, and CFI values greater than or equal to .95 were evaluated as indicating adequate model fit.

Before testing the proposed models, our first analysis focused on the antecedents of intentions (paralleling the exploratory factor analysis above). Overall, the model showed satisfactory levels of fit, χ^2 (179) = 438.61, p < .01, CFI = .91, RMSEA = .07, SRMR = .06. All factor loadings were significant and an analysis of the modification indices indicated that the three largest sources of misfit were from three unresolved covariances between self-efficacy items 2 and 3, attitudes towards moderating highway speed items 3 and 4 (both reverse coded), and attitudes towards saving fuel items 1 and 4. Allowing these residuals to covary resulted in a model with acceptable fit, χ^2 (176) = 335.13, p < .01, CFI = .95, RMSEA = .05, SRMR = .05, that was significantly better than the model without the correlated residuals, $\Delta\chi^2$ (3) = 103.48, p < .01, ΔCFI = .01.

The measurement model for the proposed hypotheses was tested by adding the intention and eco-driving items to the previous specified model. The resulting model showed satisfactory fit, χ^2 (471) = 813.21, p < .01, CFI = .92, RMSEA = .05, SRMR = .06. An examination of the modification indices indicated that several TPB items might have secondary loadings upon intentions; however, given that these variables serve as antecedents of intention in the TPB model, these loadings were not freed. However, modification indices also indicated unresolved covariance between subjective norms items 1 and 4. Allowing these item residuals to covary resulted in a significant improvement in fit, $\Delta\chi^2$ (1) = 22.95, p < .01, ΔCFI = .01:

χ^2 (470) = 790.26, CFI = .93, RMSEA = .05, SRMR = .05. This model was retained to test hypotheses 1 through 3.

Hypothesis Testing:

Model 1 regressed eco-driving on all TPB variables. Because correlations were just changed to regression coefficients to intentions, model fit was identical to the previous model, χ^2 (470) = 790.26, CFI = .93, RMSEA = .05, SRMR = .05. Hypothesis 1, which predicted that all TPB variables would be positively related to eco-driving behavior, was partially supported. Unstandardized path coefficients are presented in Figure 9. As seen in Figure 9, attitudes toward saving fuel, self-efficacy, and intention were significantly related to eco-driving behavior in the expected direction but the relationships for attitudes towards moderating highway speed, controllability, and subjective norms were not.

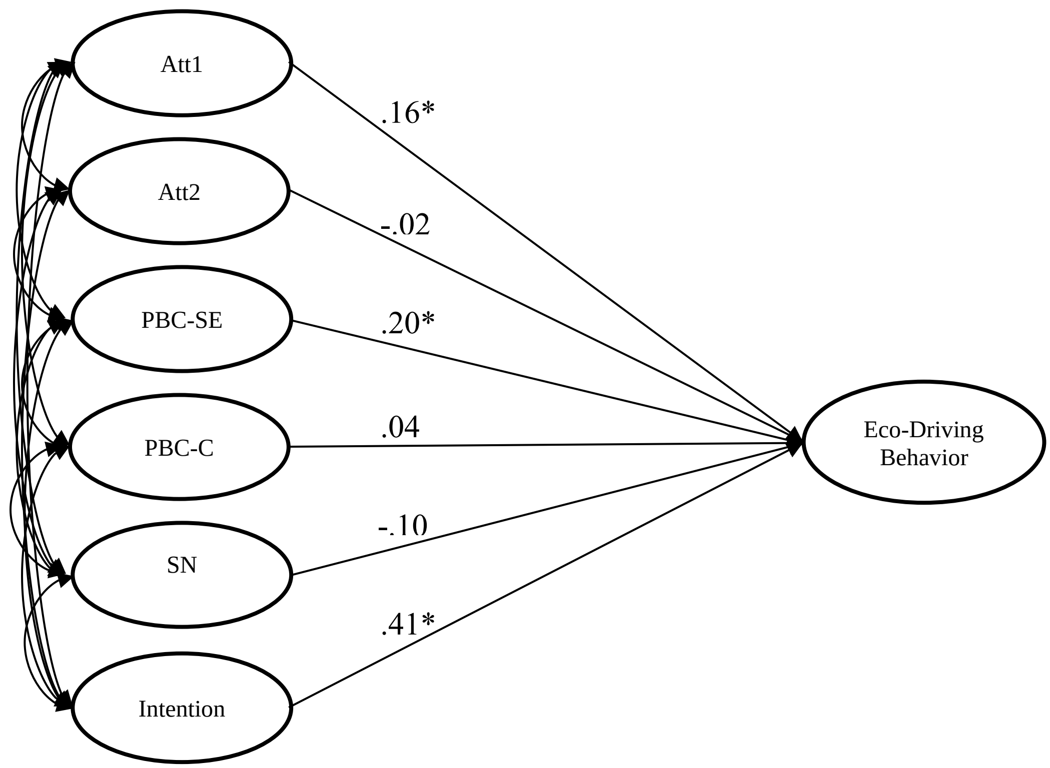


Figure 9: Model 1

Model 2 expanded Model 1 by also regressing intention onto the other TPB variables. Because all information was still retained, model fit did not change. Hypothesis 2a, which predicted that the TPB variables would act as antecedents of intentions, was partially supported. As shown in the unstandardized path coefficients presented in Figure 10, self-efficacy, attitudes towards saving fuel, attitudes towards moderating highway speed, and subjective norms were significantly related to intentions but controllability was not.

Hypothesis 2b, which stated that the TPB variables would be indirectly related to eco-driving through intentions, was partially supported. Indirect effects were estimated in lavaan by multiplying the path to intentions by the path from intentions to eco-driving. Significant indirect effects were observed for self-efficacy, indirect effect = .12, SE = .05, $z = 2.32$, $p = .02$, attitudes towards saving fuel, indirect effect = .04, SE = .02, z = 2.17, $p = .03$, and subjective norms, indirect effect = .08, SE = .04, z = 2.17, $p = .03$. Indirect effects for attitudes towards moderating highway speed, indirect effect = .01, SE = .01, z = 1.42, p = .16, and controllability, indirect effect = .00, SE = .01, z = .08, $p = .94$, were not significant.

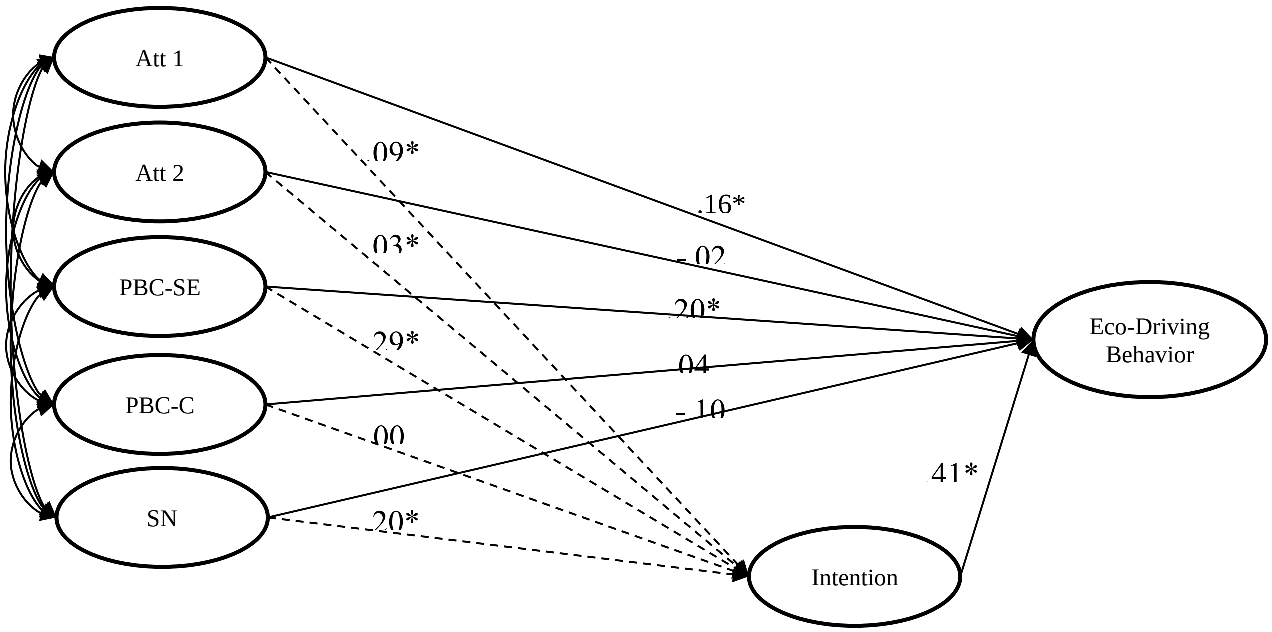


Figure 10: Model 2

Model 3 removed the direct paths between the antecedents of intentions and eco-driving behavior. Removing these paths resulted in a significant increase in misfit, $\Delta\chi^2$ (5) = 29.15, p < .05, ΔCFI = .01; however, overall model fit was still satisfactory, χ^2 (475) = 819.42, CFI = .92, RMSEA = .05, SRMR = .06. The significant increase in misfit from Model 2 to Model 3 fails to support Hypothesis 3, that intentions would fully mediate the relationship between the other TPB constructs and eco-driving. Examination of modification indices indicated that the largest source of misfit was the direct path between eco-driving behavior and attitudes toward saving fuel. Adding this direct path resulted in a modified Model 3 that did not fit significantly worse than Model 2, $\Delta\chi^2$ (4) = 5.37, p = .25, ΔCFI = .00. This model and the unstandardized path coefficients are presented in Figure 11.

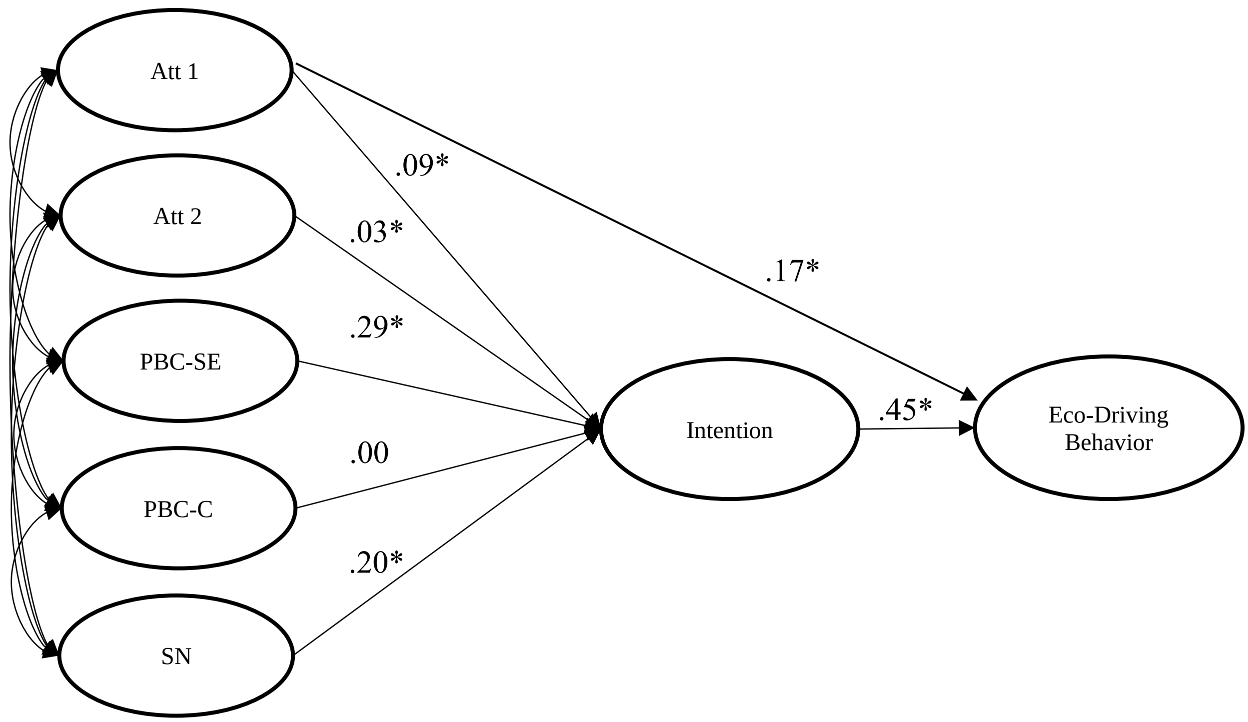


Figure 11: Modified Model 3

This modified Model 3 partially supports Hypothesis 3. The effects of attitudes towards saving fuel on eco-driving is only partially mediated by intention, with both the direct effect, b = .17, SE = .04, z = 4.47, p < .01, and the indirect effect, indirect effect = .04, SE = .01, z = 3.06, p < .01, significant. The effects of self-efficacy, indirect effect = .13, SE = .04, z = 3.40, p < .01, and subjective norms, indirect effect = .09, SE = .03, z = 3.25, p < .01, were fully mediated through intention and the indirect effects were significant.

Discussion

As noted by Barkenbus (2010), eco-driving is an overlooked climate change initiative. This is important given the size of the civilian, corporate, and government fleets of automobiles on the roads. We would additionally expand upon this further, in that fuel efficiency intentions are not limited to automobile operators, but could be an ecologically friendly factor for other transportation workers like truck drivers or pilots. With transportation accounting for 28% of the US's energy use (EIA.gov), promoting fuel efficiency intentions could have global results for reducing costs associated with fuel and in reducing CO2 omissions. While we believe that understanding and promoting fuel efficiency is a promising step towards meeting these goals, we acknowledge that research on the human side of fuel efficiency is lacking and that this study only narrowly examines civilian automotive drivers.

Utilizing TPB, we developed measures of subjective norms, attitudes towards fuel efficiency, attitudes towards moderating highway speeds, self-efficacy of saving fuel, and controllability of fuel consumption. Results conformed to past TPB research in the ecological psychology literature (Bamberg et al., 2003; De Leeuw et al., 2015), in that the theory of planned provided a useful framework for explaining eco-driving behavior. Specifically, with the exception of perceived controllability, each of the other variables had a significant impact on intentions to save fuel. Not only did attitudes towards saving fuel and intentions predict eco-driving (see Figure 11), significant indirect effects were observed for subjective norms, self-efficacy, and attitudes towards saving fuel through intentions.

Beyond its explanatory power in understanding behavior, TPB offers another important advantage in understanding ecological behaviors. Subjective norms, attitudes, and perceptions are malleable. Interventions can target these antecedents of intentions. While future studies should evaluate interventions targeting these constructs to provide additional evidence of internal validity, several studies have examined eco-interventions utilizing TPB (see Bamberg & Möser, 2007, and Steg & Vlek, 2009, for reviews). If these patterns hold for the current area, interventions aimed at the human side of increasing fuel efficiency can have a strong impact on overall fuel use.

Limitations and Future Directions:

There are several limitations that should be noted about the current study. First, although ample evidence supports the internal validity of TPB, the current cross-sectional design limits causal evidence. That is, although our data is consistent with the causal models implied in Figures 9, 10, and 11, the study design limits our discussion to just interpreting the relationships between these variables. Future research should utilize longitudinal studies similar to Lauper, Moser, Fischer, Matthies, and Kaufmann-Hayoz (2015) or intervention studies similar to those reviewed by Steinmetz, Knappstein, Ajzen, Schmidt, and Kabst (2016) to provide further support of the causal inferences regarding fuel efficiency. Such research would go a long way in supporting efforts towards both small- and large-scale fuel efficiency initiatives based on TPB variables.

We sought to target a diverse population of civilian automotive drivers by recruiting participants from reddit forums devoted to automobiles, the crowd sourcing platform mTurk, and college students at a Midwestern university. While this increases the external validity of the results when applied to a diverse civilian population, the diversity between participants likely adds noise to our model estimates and limits our ability to estimate its transfer to corporate or military fleets. Future research should further examine whether this model towards eco-driving is supported among transportation employees' driving behavior and in environments where fuel-efficiency initiatives already exist.

Finally, interpretation of results is limited by the measure of eco-driving behavior. While several studies have utilized in-vehicle sensors (e.g., Beusen et al., 2009) and simulations (Zhao, Wu, Rong, & Zhang, 2015) to study eco-driving/fuel-efficiency, for this initial investigation we focused on self-reported behavior. While such measures have the potential of being distorted, steps were taken to reduce this to a minimum. First, the eco-driving items were presented in a list of 13 driving behaviors with participants simply instructed to report how often they engaged in each behavior and fuel efficiency had not been mentioned. Participants had been recruited to participate in a study looking at driving behaviors. Second, eco-driving behaviors were rated prior to completing the TPB construct measures, which explicitly mentions saving fuel and fuel efficiency. These steps were taken to reduce potential social desirability bias in these ratings – we hoped driving behaviors by themselves would be more neutral than questions tied to fuel efficiency. Future research should evaluate the relationship between this type of measure and actual driving behaviors.

Paper 3: Predicting Pro-Environmental Behavior in USAF Cargo Pilots

Introduction:

Aircraft are a large consumer of petroleum; the real-world impacts of aircraft emissions, whether from local pollution or contributions to climate change, are difficult to calculate in solely financial terms. A 2014 study conducted at the Massachusetts Institute of Technology (MIT) estimated that aircraft emissions are responsible for 210 deaths and $1.4 billion in lost value every year, calculated in year 2000 dollars (Brunelle-Yeung et al., 2014). These calculations were based on health effects derived from particulate emissions, such as premature mortality, chronic bronchitis, and cardiovascular damage, rather than effects from aviation's contributions to climate change (Brunelle-Yeung et al., 2014). Aviation passenger transport in 2018 generated 918 million metric tons of carbon dioxide (CO2), representing 2.4 percent of total global CO2 emissions, an increase of 32 percent over the past five years, and was 70 percent higher than projected (Graver et al., 2019).

In addition to the negative environmental effects resulting from burning jet fuel, the fuel itself is hazardous to the health of humans and the local ecosystem. United States Air Force (USAF) airmen handling jet fuels like JP-8 or Jet-A can be exposed via skin contact, vapor inhalation, or micro-droplet ingestion, potentially resulting in damage to the nervous, respiratory, and gastrointestinal systems (CDC, 2017). In laboratory animals, jet fuel exposure has led to liver damage, decreased immune system response, hearing damage, and impairment of neurological functionality (CDC, 2017). The US Department of Defense (DoD)'s Petroleum Systems Maintenance document instructs against allowing skin contact with liquid petroleum fuels, as contact can cause drying, chapping, and cracking (DoD, 2017). Accidental ingestion of fuel material may cause central nervous system depression and pneumonia (DoD, 2017). While these risks are certainly higher for those who work directly with fuels than they are for local stakeholders, it remains prudent to pursue avenues of fuel conservation nonetheless.

The USAF, as part of the DoD and US Government, safeguards America's interests both present and future; to safeguard the future it is necessary to reduce ecological externalities imposed by the burning of fossil fuels. This is particularly difficult for the USAF, as it is the service whose mission is most dependent on petrochemical availability. With current technology, only petrochemical fuels enable large-scale operationalization of aviation. Other services' modes of transportation, such as land-based (US Army) and sea-based (US Navy) certainly are major consumers of petrochemicals, but their primary domain is not as severely constrained by energy source as the USAF.

While the United States Environmental Protection Agency (EPA) does not provide statistics for jet fuel-based pollution emitted by the DoD, a study by Crawford (2019) analyzes DoD-reported fuel consumption and calculates an emissions figure in CO2-equivalent. The results indicate the US DoD's 2017 jet fuel consumption alone contributed 28.5 million tons of CO2-equivalent (MTCO2e), which exceeds the MTCO2e figure of entire nations like Croatia (23.5 MTCO2e) and Honduras (21.1 MTCO2e). The pollution figures from the entire US DoD, including jet fuel consumption, gasoline, electricity consumption, and other miscellaneous pollution sources are even more sobering. The US DoD contributed 59 MTCO2e in 2017, compared with the emissions of entire nations like Ireland (59.2 MTCO2e), Sweden (50.8 MTCO2e), and Norway (46.6

MTCO2e) (Crawford, 2019). Calculated most generously, including active duty, reserve, civilians, etc., the DoD employs 3.4 million personnel, still over a million fewer than the population of Ireland in 2017 (4.75 million) (Worldometers.info, accessed 2019). It therefore stands to reason that US DoD personnel have an outsize individual influence on energy consumption compared with the average citizen in the countries mentioned above, especially considering the administrative influence wielded by many personnel in the DoD such as officers, senior non-commissioned officers, and high ranking civilian personnel.

Due to its unique position as a major air freight mover and public servant, the onus falls on the USAF to answer these key questions: can pilots' conscious choices meaningfully affect sortie fuel consumption, and if so, what explains these behaviors, and what implications does this hold?

Most of the total energy used in the sortie is consumed to execute the actual flight: to lift the load, fly to the destination, approach the pattern, land, etc. Pilots have some discretionary influence over fuel usage; they can, within boundaries, determine cruise altitude and cruise speed, as well as choosing how many engines to run during taxiing. Schumacher (2015) conducted analysis on discretionary fuel usage, and found the most effective metric for estimating it is one which corrects for payload discrepancies (Schumacher, 2015). Since US carriers consumed 17.87 billion gallons of fuel in 2018 (Mazareanu, 2019) even a one percent savings would result in saving 180 million gallons annually, or about 387 million US dollars.

Many pilots on US carriers learned to fly in the USAF. In 2015, C-130J and C-17 pilots alone, flying channel airlift missions, flew 62 million ton-miles of cargo across the globe. In this small overall sample, these aircraft burned 16M gallons of fuel, translating into $48 million US dollars overall. In the larger picture, USAF cargo aircraft overall used $4 billion of fuel in 2017; a reduction of one percent would have saved US taxpayers $40 million before factoring in environmental benefits.

This study explores the little-investigated territory of fuel-efficient behavior in aircraft pilots. We measure the attitudes, perceived behavioral control, and subjective norms of pilots. We compare those to both intention and each pilot's fuel efficiency history to determine what drives fuel-efficiency. We access records of each mission including planned fuel usage and actual fuel usage. With this data we can calculate a fuel metric for each pilot and estimate the variability in pilot fuel efficiency.

It is important to explore every avenue for garnering energy savings to reduce environmental impact, save money, and reduce stress on the supply chain. Since air transport depends on petroleum, the fuel-efficient behavior of pilots is of critical importance.

The Theory of Planned Behavior is commonly used to understand pro-environmental behavior. It is a model of understanding conscious, deliberate decision-making directly influenced by intention. In turn, intention itself is predicted by attitudes towards the behavior, perception of one's level of control over the behavior, and the perception of social norms relating to the behavior. Analyses of the TPB literature indicates the TPB consistently explains deliberate behavior as a direct descendant of intention (Bamberg and Moser, 2006) and the TPB's reliability means it is regularly included in meta-studies of pro-environmental behavior in general (Klockner, 2013; Lanzini, 2017). We contribute to the understanding of pro-environmental behavior of workers and extend that literature by studying workers in their primary task. An understanding of pilots' motivations to save fuel enables us to design, and weigh the costs of, interventions to encourage all pilots to be similarly efficient.

Literature Review:

Certain models argue that pro-environmental behavior is shaped more by factors external to the individual, like social pressure, rather than internal factors like attitudes and perceptions. Clayton and Brook (2005) posit a social-psychological model for behaviors related to conservation and eco-friendliness, suggesting that situational context is the primary behavioral driver. Under this model, internal factors like attitudes, perceptions, knowledge, and motivations serve to modify the main relationship between situational context and behavior. To reduce the variability imparted by situational context, we chose only a sample of sorties flown as standard channel cargo missions. No combat zone or special airlift missions were considered.

Theory of Planned Behavior. Figure 12 shows the Theory of Planned Behavior, or TPB (Ajzen, 1985), which explains human behavior as a direct result of human intention towards that behavior. In turn, intention results from three antecedents: attitude towards the behavior, perception of social norms surrounding the behavior, and perception of one's level of control over enacting the behavior. The TPB differs from its direct ancestor, the Theory of Reasoned Action (TRA) (Fishbein and Ajzen, 1975; Ajzen and Fishbein, 1980) by the presence of this last psychological construct, perceived behavioral control (PBC). In many uses of the TPB, PBC has been shown to moderate the antecedent-dependent relationship between intention and behavior.

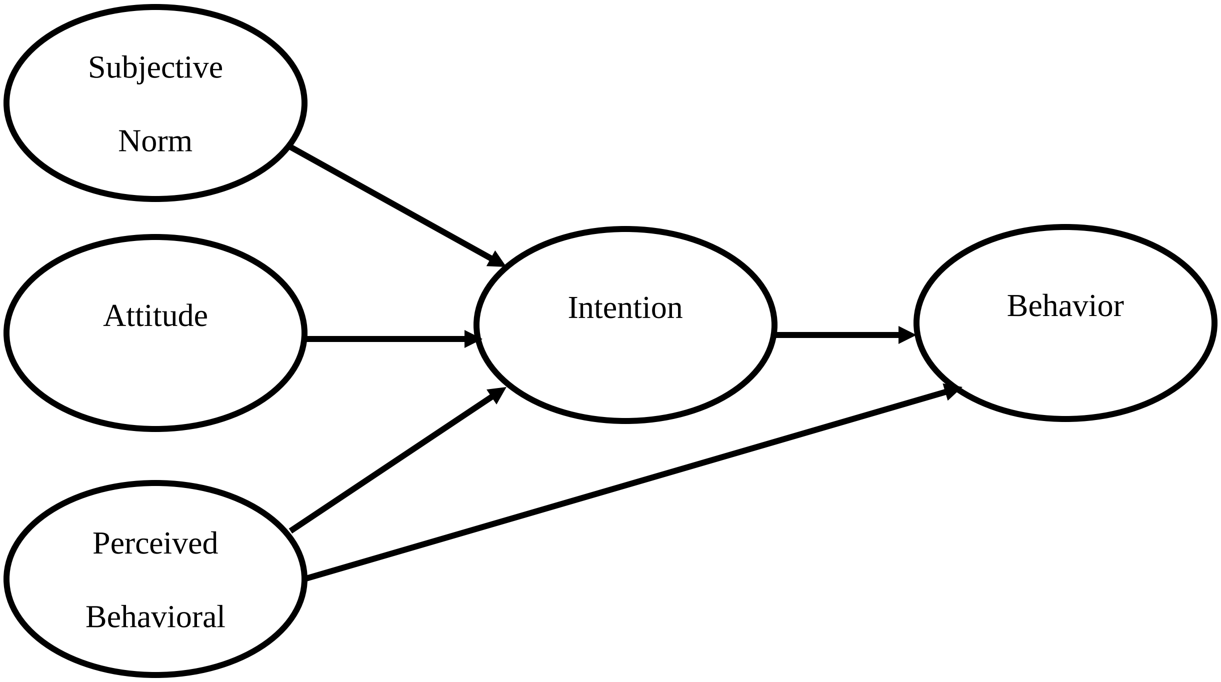


Figure 12: Theory of Planned Behavior (Ajzen, 1985)

The Theory of Planned Behavior has been successful in predicting deliberate, choice-based behavior. It regularly appears in literature surrounding pro-environmental behavior (PEB) studying individual and corporate behavior alike. Other behavioral models, like the norm-activation theory (NAM), overlap with the TPB in that they incorporate perceived social or personal norms, but struggle to explain or predict specific behaviors.

Intention. In the TPB, Intention is the sole direct antecedent of behavior. Intention shares a positive relationship with behavior; the higher the level of intention to perform the behavior, the stronger likelihood exists that the subject will perform that behavior (Ajzen, 1991). Intentions capture the motivational factors which influence behavior, and are therefore the necessary component of the TPB which allows explanation and prediction of specific rather than generalized behaviors (Ajzen, 1991).

Hypothesis 1 (H1). Pilots who display higher levels of intention to fly in a fuel efficient manner are more likely to conserve more fuel while flying.

Attitude. Attitude represents an individual's tendency to respond in a consistent manner, favorable or unfavorable, to a particular concept (Fishbein and Ajzen, 1974). In addition, Fishbein and Ajzen (1974) found that attitudes are not direct causes of behavior but rather influence intentions. Ajzen (2002) recommends rather than measuring Attitude as a single construct, it is more useful to measure it with two components. The first component (ATT1_IN) is instrumental, measuring the subject's evaluation of the behavior's overall worth. This is reflected in items such as *valuable – worthless* or *harmful – beneficial*, adjectives centered on the behavior's efficacy. The second component (ATT2_EX) is experiential, measuring a more subjective take on the behavior. These items measure the experience of performing the behavior with adjective pairs like *pleasant – unpleasant* and *enjoyable – unenjoyable* (Ajzen, 2002).

Hypothesis 2 (H2). (a) Pilots with positive attitudes towards the instrumental component of saving fuel while flying (Is it worthwhile? Is it beneficial?) are more likely to have positive intentions toward saving fuel.

(b) Pilots with positive attitudes towards the experiential component of saving fuel while flying (Do I enjoy it? Is it pleasant?) are more likely to have positive intentions toward saving fuel.

Subjective Norm. Subjective Norm (SN) is the perception of social pressure in relation to the subject performing – or not performing – the behavior in question (Ajzen, 1991). These norm(s) are the beliefs one holds towards other people's expectations whether or not to perform the behavior (Ajzen, 1992). Subjective norms also are predictor of intention to perform a behavior rather than direct predictors of behavior. (Ajzen, 1991).

Hypothesis 3 (H3). Pilots who perceive more social pressure to fly fuel-efficiently will exhibit higher levels of positive intentions towards saving fuel.

Perceived Behavioral Control. The motivational influence represented by Intention is only capable of predicting behavior if the subject is actually able to perform the behavior in question. This construct involves subjects' perceptions of the feasibility of performing the behavior being studied, and is therefore an internal locus of control. Examples of external loci of control are hindrances such as money, time, external cooperation, and aerodynamic drag (RAND, 2015) which restrict the subject's ability to perform the behavior in the real world (Ajzen, 1991). Perceived behavioral control (PBC) represents the ease or difficulty of performing the behavior of interest (Ajzen, 1991). PBC is sometimes positioned in the TPB literature as an antecedent to behavior (Ajzen, 1991); however, as a predictor PBC exerts less influence on PEB than INT does (Ajzen, 2012). Regardless, PBC demonstrates good predictive capabilities for intention (Ajzen, 2001) and is generally measured by asking direct questions about capability to perform a behavior, or by indirectly asking about beliefs regarding inhibiting or facilitating factors (Ajzen, 2002). PBC is strongly related to Bandura's (1977; 1982; 1986) concept of self-efficacy which influence human decision making, degree of effort put forth, perseverance, and thought patterns both positive and negative (Bandura 1986). We split PBC into two constructs as it is represented in TPB literature: self-efficacy and controllability. Self-efficacy (PBC1_SE) defines the perception of performing the behavior in question upon an "easy – difficult" spectrum. Controllability (PBC2_CN) defines the perception of performing the behavior in question in more structural terms, such as asking whether or not the subject perceives sufficient processes exist to allow the behavior to be performed at all. The third sub-construct, Feedback (PBC3_FB), was added to represent the perception of information resources available to the pilot which may facilitate the performance of the behavior. This construct was written and pilot tested by Cotton et al. (2016).

Hypothesis 4 (H4). (a) Pilots who believe that they will have an easier time flying fuel-efficiently will be more likely to have positive intentions towards flying fuel-efficiently.

(b) Pilots who believe that processes and other organizational hurdles will not hinder their efforts to fly fuel efficiently, will be more likely to have positive intentions towards flying fuel-efficiently.

(c) Pilots who believe they are provided with appropriate amount of feedback to know how efficiently they are flying, and have flown once the sortie ends, will be more likely to have positive intentions towards flying fuel-efficiently.

Research Questions. This study intends to investigate the following:

(a) Can a pilot's actions and decisions account for a meaningful portion of channel mission fuel consumption?

(b) Does there exist meaningful variance among different cargo pilots for explaining fuel consumption?

(c) Finally, can any of this variance be explained by attitudes, knowledge, beliefs, and perceptions intrinsic to pilots?

Methodology

Data Collection. The Antecedents of Fuel Efficiency Survey (Cotton et al., 2016) was distributed to 415 aircraft commanders starting 1 Jul 2019, via SurveyMonkey.com. Of the 415 contacted, 62 (14.9%) returned completed questionnaires. The sample characteristics are detailed in Table 7 below.

Demographic Category	Respondents	Percentage
Gender	Male: 60 Female: 2	Male: 96.8% Female: 3.2%
Rank	Captain: 18 Major: 35 Lt. Col: 10 Colonel: 1	Captain: 29% Major: 56.5% Lt. Col: 16.1% Colonel: 1.6%
Aircraft Flown	C-130J Hercules: 22 C-17 Globemaster III: 30 C-5 Galaxy: 10	C-130J Hercules: 35.5% C-17 Globemaster III: 48.4% C-5 Galaxy: 16.1%

Table 7: Sample Characteristics.

Potential subjects were identified through historical USAF sortie data. Our target population was only those pilots who flew channel cargo missions, which are missions devoted to bringing cargo from departure destination to arrival destination on known routes. In order to minimize unexplained variability, we did not include sorties flown as part of contingency operations, whether combat, humanitarian, or other expedited designation. Respondents were asked to provide first name, last name, rank, aircraft flown during the specified time period, unit, and experience (flying hours) in that airframe. None of the subjects received any direct compensation for their participation in the survey, financial or otherwise.

Method of Analysis. Wetzels et al. (2009) demonstrate that partial least squares structural equation modeling (PLS-SEM) is a suitable and desirable approach to modeling hierarchical models such as models of behavior. As defined in the study, the difference between covariance-based SEM (CB-SEM) and PLS-SEM is that CB-SEM intends to minimize the maximum likelihood fitting function between the sample and implied (parameter) matrices (Wetzels et al., 2009; 190); PLS-SEM by contrast intends to minimize the variance of its dependent variables, latent and manifest alike (Wetzels et al., 2009; 190). The authors give the example of customers shopping at online book and CD retailers. “Experiential Value,” or the value customers extract from their purchase, in Wetzels et al. (2009) is a fourth-order construct composed of two individual sub-constructs, “Hedonic Value” and “Utilitarian Value.” Each of those sub-constructs is in turn composed of multiple sub-constructs, and so on. Their measurement items all demonstrated strong factor loading while composite reliability (CR) was greater than 0.8 for all constructs (Wetzels et al., 2009). The authors suggest goodness-of-fit (GOF) values for PLS-SEM as $GOF_{small} = 0.1$, $GOF_{medium} = 0.25$, and $GOF_{large} = 0.36$, measurements claimed by the authors as suitable for CB-SEM as well (Wetzels et al., 2009).

Hair et al. (2011) outlines situations in which PLS-SEM is most appropriate and also provides examples of the process’ limitations. The authors draw a contrast between CB-SEM and PLS-SEM based on the differing mathematical objectives of each method. CB-SEM compares observed and predicted covariance matrices and measures their differences (Hair et al., 2011). PLS-SEM instead focuses on investigating and maximizing the explained variance of the dependent latent variables (Hair et al., 2011).

Despite these seemingly opposing mathematical approaches, the authors stress that the most important difference between these approaches is philosophical, rather than mathematical. Since CB-SEM develops a theoretical model and then examines the findings' relationship to it, it is better suited for CFA and testing theories. PLS-SEM, with its greater similarity to multiple regression analysis and use of R-square, demonstrates superior predictive capability and is superior for theory development (Hair et al., 2011).

Afthanorhan et al. (2013) clarify the mechanisms of PLS-SEM especially as it pertains to confirmatory factor analysis (CFA). The study uses two kinds of statistical software, AMOS for CB-SEM and SMARTPLS for PLS-SEM, to compare and contrast the efficacy of both approaches. Like Wetzels et al. (2009), Afthanorhan (2013) uses a hierarchical model from the social sciences; here, the dependent variable is a second order "Motivation" construct. Factor loadings as compared between CB-SEM and PLS-SEM are generally comparable with PLS-SEM showing a slight but overall stronger set of factor loadings than CB-SEM. Average Variance Extracted (AVE) scores tended to be higher than in CB-SEM.

Hair et al. (2014) provides a review of the PLS-SEM literature in the business domain between the inception of PLS-SEM in 1974, up to 2014. In this review the authors discuss the main reasons for opting in favor of PLS-SEM vs. CB-SEM. First, PLS-SEM is better able to cope with data which does not fit a standard normal distribution than CB-SEM (Hair et al., 2014). Secondly, PLS-SEM does not require as large of a sample size as CB-SEM. CB-SEM is vulnerable to problems such as poor model fit, parameter estimates, and statistical power all stemming from subpar sample size (Hair et al., 2014).

A common rule of thumb suggests no fewer than 200 respondents for a CB-SEM model, whereas comparable PLS-SEM models may retain good model fit, statistical power, and parameter estimates as low as 50 respondents.

Hair et al. (2010; 2011; 2014) describe PLS-SEM models as consisting of two conceptual halves - the inner, or structural, model, and the outer, or measurement model (Hair et al., 2014). The inner model is comprised of the structural paths between the various constructs, while the outer model is comprised of individual items and constructs to which they point. Constructs located "upstream" are considered formative, while constructs located "downstream" are considered reflective (Hair et al., 2014). PLS-SEM, due to its mathematical ties to linear regression, generally demonstrates better predictive capabilities than its counterpart CB-SEM (Hair et al., 2010; 2011; 2014). It must be remarked that neither approach is necessarily "better" or "worse" than the other. Choosing between CB-SEM and PLS-SEM is a matter of selecting which tool is more appropriate for the job.

Measures. The instrument used in this study was built and pilot-tested by Cotton et al. (2016), and consisted of 78 items. Responses were collected between the months of June, July, and August of 2019. A total of 100 responses were obtained. After eliminating incomplete and duplicate responses, the remaining data comprised 62 pilots and 476 sorties flown. Pilots flew a channel mission at least once during the observation period between August 2014 and June 2016. Accordingly, there are multiple sorties and corresponding fuel scores. In the initial analysis, we aggregated fuel scores by taking the average of the scores, generating one record per pilot. However, disaggregating fuel scores, and thus having a sample size based on sorties rather than pilots makes for a more statistically robust analysis. To that end, we matched a pilot's survey response to his or her fuel scores on a per-sortie basis.

Dependent Variable. The fuel consumption per sortie was evaluated using a metric developed by Schumacher (2015). Previous research by Reiman (2014) employed regression analysis to project aircraft fuel consumption given factors such as great circle distance and payload, taken from USAF records. Great circle distance is calculated around the globe of the Earth from departure location to arrival location (Reiman, 2014). Other components include deltas between planned and actual fuel payloads (on the ramp, at takeoff, and at landing), and delta between planned and actual cargo weight. Building upon the research of Reiman (2014), Schumacher (2015) indicates that a metric which corrects for the discrepancy between planned and actual cargo weight was an effective measure of discretionary fuel burn. The main limitation of the metric sourced from Schumacher (2015) is that it does not entirely isolate discretionary fuel variance from fuel variance induced by other factors, such as weather. Nevertheless, payload delta represents a significant source of non-discretionary fuel variance, and a metric which controls for this source allows for more accurate results than one which does not. A negative value on the fuel score indicates that less fuel was consumed than planned; therefore, a negative relationship between INT and the fuel score would indicate that pilots who intend to save fuel will save fuel.

Results:

This study employed a partial least square structural equation modeling (PLS-SEM) method, a component-based SEM, for predicting pilots' eco-friendly behavior. SmartPLS 3.0 (Ringle et al., 2015) was used for analyzing data, applying a bootstrapping approach with 1,000 random subsamples in order to assess the significance of the tested model.

Measurement Validation:

Procedural and statistical remedies were employed to alleviate common method bias issues, as proposed by Podsakoff et al. (2003). No serious issue was found in the data set. For construct reliability and validity, several approaches were attempted. As shown in Table 8, Cronbach's alpha values exceeded 0.6 for each construct, and composite reliability measures are larger than 0.8. Accordingly, these figures confirm the internal consistency of the constructs employed.

	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)
ATT1	0.866	0.942	0.915	0.783
ATT2	0.624	0.627	0.842	0.727
INT	0.857	0.863	0.913	0.778
PBC1	0.675	0.982	0.843	0.732
PBC3	0.745	1.047	0.875	0.779
SN	0.814	0.828	0.876	0.638
PEB	1.000	1.000	1.000	1.000

Table 8: Construct Reliability and Validity.

As presented in Table 9, the Fornell-Larcker criteria indicate no major issues on the constructs' discriminant validity. The correlations across the constructs are less than the square roots of the shared variance between the constructs and their measures, which supports convergent and discriminant validity (Fornell and Larcker, 1981).

	ATT1	ATT2	INT	PBC1	PBC3	PEB	SN
ATT1	**0.885**						
ATT2	0.395	**0.852**					
INT	0.275	0.370	**0.882**				
PBC1	0.036	0.048	0.310	**0.856**			
PBC3	-0.242	-0.175	-0.127	0.150	**0.882**		
PEB	-0.010	-0.076	-0.116	-0.008	-0.028	**1.000**	
SN	0.608	0.470	0.627	0.156	-0.051	-0.077	**0.799**

Table 9: Discriminant Validity: Fornell-Larcker Criterion.

According to Henseler et al. (2015), Heterotrait-Monotrait (HTMT) ratios are superior to the Fornell-Larcker criterion for detecting discriminant validity issues. HTMT ratios confirm the discriminant validity of the constructs as demonstrated in Table 10.

	ATT1	ATT2	INT	PBC1	PBC3	PEB	SN
ATT1							
ATT2	0.559						
INT	0.298	0.507					
PBC1	0.271	0.086	0.372				
PBC3	0.285	0.199	0.158	0.154			
PEB	0.017	0.098	0.127	0.029	0.041		
SN	0.719	0.660	0.715	0.339	0.173	0.103	

Table 10: Discriminant Validity: Heterotrait-Monotrait (HTMT) Ratio.

For an additional measure of discriminant validity, cross loadings of all items are examined. There is no serious issue as presented in Table 11.

	ATT1	ATT2	INT	PBC1	PBC3	PEB	SN
ATT1-IN1	**0.905**	0.287	0.309	0.022	-0.192	0.004	0.571
ATT1-IN3	**0.832**	0.390	0.202	0.079	-0.230	-0.035	0.515
ATT1-IN4	**0.915**	0.414	0.179	-0.006	-0.234	-0.003	0.511

ATT2-EX2	0.296	**0.866**	0.328	0.010	-0.162	-0.037	0.493
ATT2-EX5	0.381	**0.839**	0.301	0.074	-0.135	-0.095	0.300
PEB Score	-0.010	-0.076	-0.116	-0.008	-0.028	**1.000**	-0.077
INT2	0.276	0.302	**0.887**	0.305	-0.202	-0.178	0.528
INT3	0.267	0.330	**0.915**	0.154	-0.093	-0.006	0.678
INT4	0.178	0.349	**0.842**	0.379	-0.033	-0.127	0.440
PBC1-SE3	0.281	0.055	0.150	**0.745**	-0.015	0.021	0.283
PBC1-SE4	-0.081	0.037	0.333	**0.953**	0.200	-0.020	0.073
PBC3-FB2	-0.258	-0.226	-0.138	0.170	**0.958**	-0.015	-0.122
PBC3-FB3	-0.138	-0.017	-0.066	0.064	**0.799**	-0.047	0.112
SN1	0.604	0.476	0.550	-0.001	-0.129	0.019	**0.839**
SN2	0.286	0.290	0.538	0.365	0.034	-0.132	**0.783**
SN4	0.507	0.419	0.309	-0.075	0.020	-0.086	**0.761**
SN7	0.563	0.339	0.533	0.130	-0.061	-0.061	**0.811**

*: There is only one item or a measure of fuel efficiency.

Table 11: Discriminant Validity: Cross Loadings.

Correlations between constructs are assessed using confirmatory factor analysis (CFA). Table 12 exhibits construct correlations.

ATT1							
ATT2	0.395						
INT	0.275	0.370					
PBC1	0.036	0.048	0.310				
PBC3	-0.242	-0.175	-0.127	0.150			
PEB	-0.010	-0.076	-0.116	-0.008	-0.028		
SN	0.608	0.470	0.627	0.156	-0.051	-0.077	

Table 12: Construct Correlations.

Variance inflation factors (VIF) for items and constructs in the CFA model do not exceed 5.0, which generally indicates that collinearity is not a serious issue for our analysis. Standardized root mean square residual (SRMR) is 0.102 for the CFA model, which is greater than the desired threshold of 0.08. While this threshold is not an absolute measure, this is still slightly outside the desired boundary. Pro-Environmental Behavior

(PEB) is negatively coded such as negative numbers for fuel savings, meaning the negative correlation between INT and PEB (significant at $\alpha = 0.01$) indicates INT predicts fuel savings. Figure 13 displays the model chosen for structural analysis as a result of the CFA.

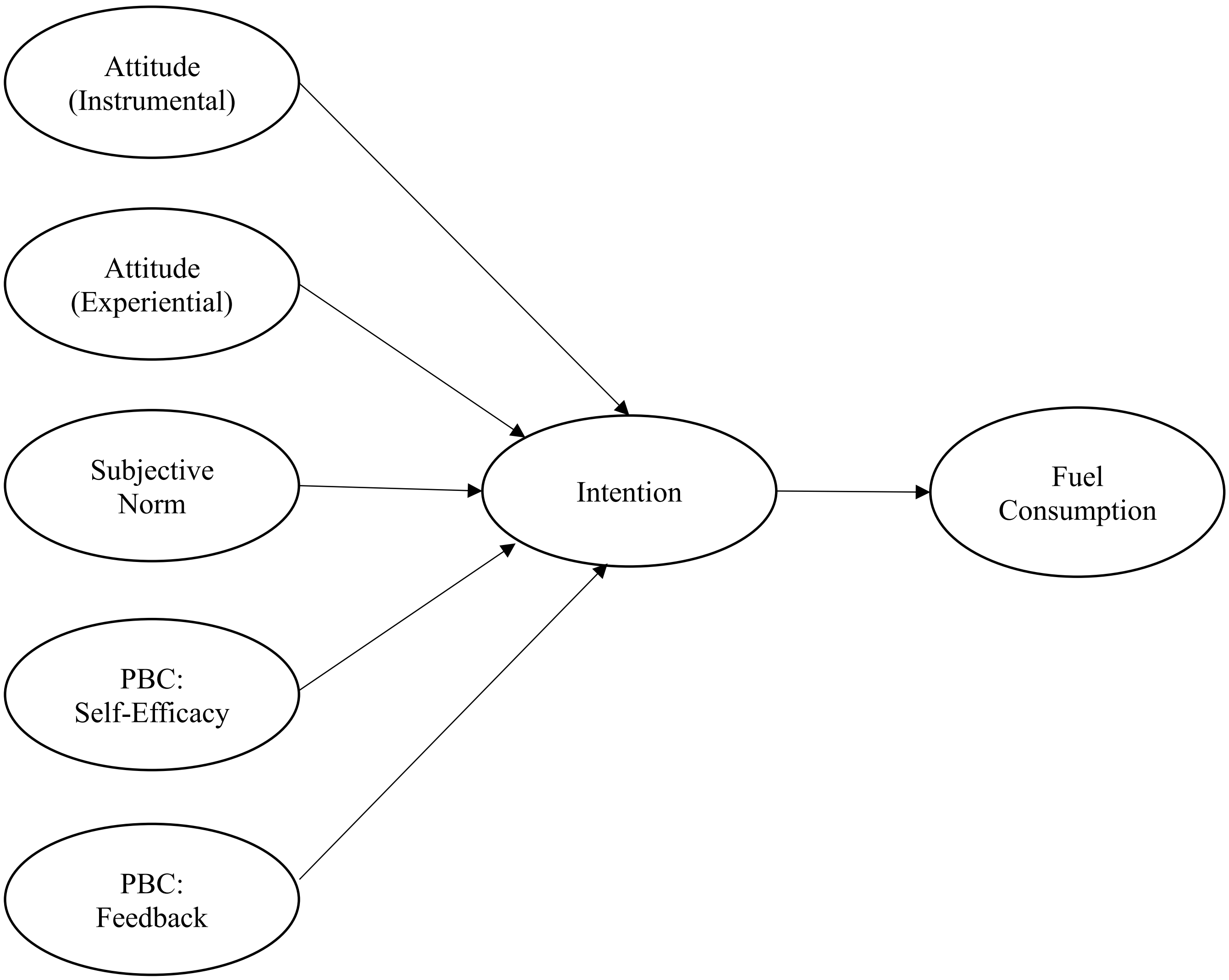
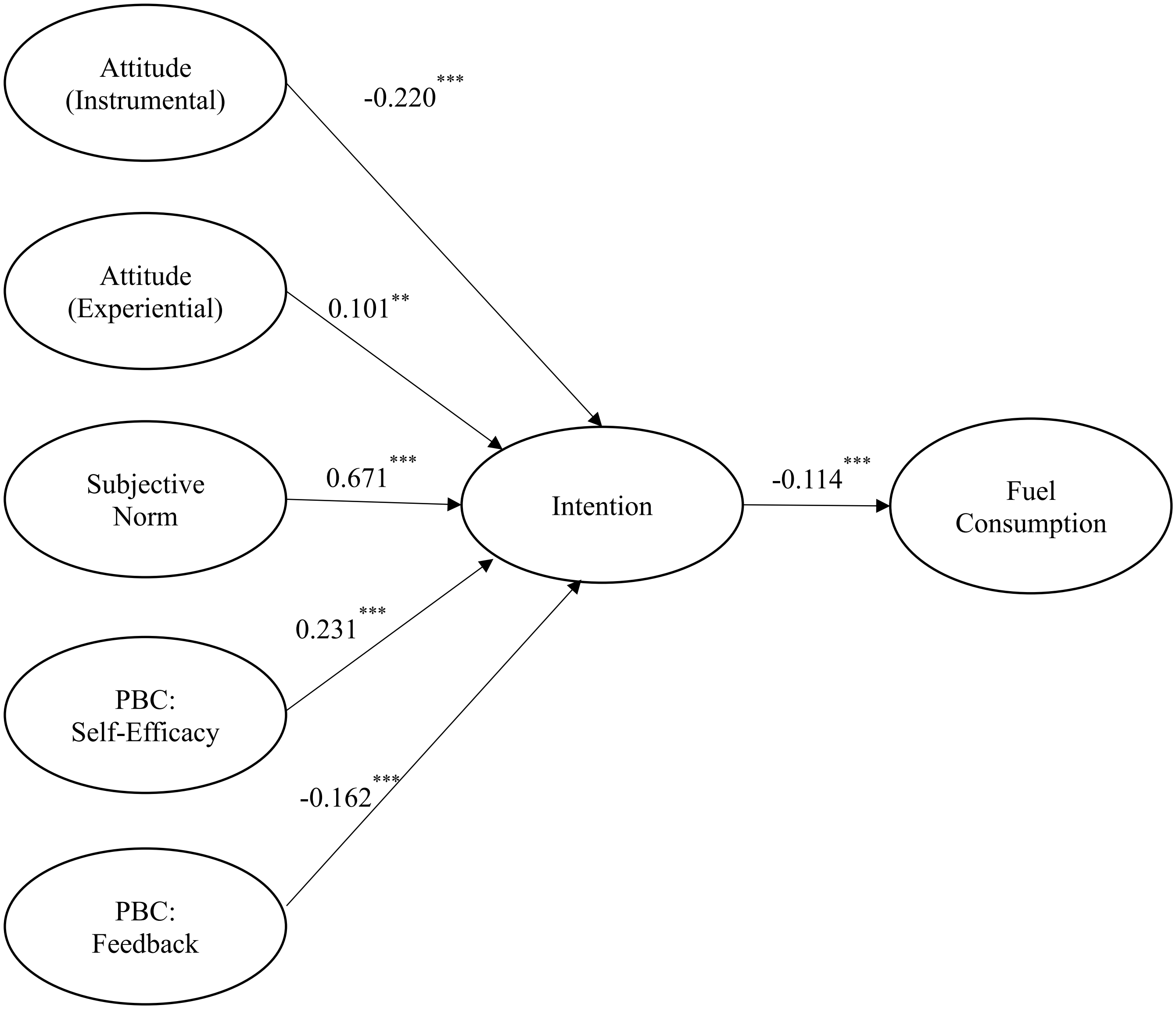


Figure 13: Proposed Model

Structural Model Results. Our study aims to test the hypotheses on cargo pilots' fuel saving behaviors, and, at the same time, attempts to explore a TPB-based model for predicting behaviors (Ajzen, 1985).

Structural Model. The model used examines relationship between the constructs that precede actual fuel saving behaviors or PEB. Figure 14 shows the result of our model estimated with the PLS algorithm and bootstrapped 1,000 times for the significance of path coefficients. Sensitivity analysis for the fuel delta metric was performed by testing whether the removal of fuel delta scores outside of three standard deviations, or 3-sigma, would have a significant effect on the results. To perform the test, 14 fuel delta outliers were removed from the data set and the model was re-run. The levels of significance were unchanged following the sensitivity analysis, which indicates no impact on our results from outliers.



***: $p < 0.01$; **: $p < 0.025$; *: $p < 0.05$

Figure 14: Model With Path Coefficients (PLS Algorithm)

All paths are significant. Because fuel savings (PEB) are recorded as negative numbers, the coefficient between Intention and PEB is negative. A relationship strength of -0.114 and a significance of $p < 0.01$ indicates a small, but definite, antecedent-dependent relationship between pilots' intentions to save fuel and saving fuel. Furthermore, while model variants incorporating a direct PBC-PEB link as proposed in the literature were tested, no support was found for the relationship in this case, and it was dropped for parsimony.

Results on the Hypotheses:

(H1) **Result**: The structural model shows a negative relationship between intentions to save fuel, and fuel delta. This indicates that higher levels of intention to fly in a fuel efficient manner will predict using less fuel than anticipated. A relationship strength of -0.114 is considered weak. The statistical significance of this relationship is $p = 0.008$, within the most stringent of three thresholds for statistical significance. These results indicate Hypothesis H1 is **Slightly Confirmed**.

(H2a), (H3) **Result**: ATT1_IN displayed a negative relationship of -0.220 to INT, counter to the strong positive relationship commonly demonstrated between ATT1_IN and INT in TPB literature. The relationship between SN and INT was strong at 0.671. Both relationships fell within the most stringent threshold for statistical significance at $p < 0.01$. Path analysis testing after deleting SN revealed the coefficient of ATT1_IN changed from negative to positive while maintaining a similar path coefficient. This did not occur during a third test where PBC was deleted and SN was left unchanged. Such results are often indicative of multicollinearity, despite VIF scores within acceptable range. Cross loadings between ATT1_IN, SN, and INT, as shown on Table 4, indicate potential overlap between these constructs. Attitude constructs are typically the strongest and most consistent predictors of INT in TPB literature. When reviewing the mean scores by item, ATT1_IN items typically received higher scores than either SN or INT, receiving mainly 6 or 7 out of 7. The item scores for SN and INT were similar to one

another but lower, around 5 to 6 out of 7. This could potentially indicate that pilots generally have positive attitudes towards the concept of saving fuel, but the influence exerted on pilot intention by perceived social pressure nullifies any effect these positive attitudes may exert. The TPB model was chosen because of its strong backing in the literature and its emphasis on conscious, deliberate choices indicative of the judgment and decision making USAF pilots are trained to employ. The results of our structural model indicate that Hypothesis H3 is **Confirmed**, but Hypothesis H2a is **Inconclusive** due to the strong interaction between ATT1_IN and SN.

(H2b) **Result:** Experiential attitudes (ATT2_EX) did not display the same interaction with SN as ATT1_IN. The relationship between ATT2_EX and INT was weak, at 0.101. This relationship fell into the second-most stringent category for statistical significance ($p = 0.013$, $p < 0.05$). ATT2_EX items displayed lower mean scores of 4 to 5 out of 7. This could be due to how ATT2_EX links value judgments like “bad-good” to a specific behavior of “flying at max range airspeed.” This could potentially have induced a confounding factor in the survey. We judge this hypothesis as **Inconclusive.**

(H4a) **Result:** The strength of the relationship between PBC1_SE and INT was moderate, at 0.231. The relationship fell within the most stringent threshold for statistical significance of $p < 0.01$. The relationship between Self-Efficacy and Intention tends to be strong throughout TPB literature, and often manifests as overshadowing Controllability. The same effect occurred in our CFA, leading to the removal of Controllability (PBC2_CN) from the final model for parsimony. These results imply support for (H4a), as **Confirmed**.

(H4c) **Result:** The relationship between PBC3_FB (Feedback) and INT was -0.162. Its statistical significance fell within the most stringent threshold of $p < 0.01$. These results indicate a slight but inverse relationship between perceived feedback and intention to fly in a fuel efficient manner. Mean responses per item tended to be low in comparison with responses for INT, with no respondents indicating "Strongly Agree" to questions such as PBC3_FB2 and PBC3_FB3 indicated in Table 1.

(insert Table 1 about here)

These two items were the only ones in the final model which received zero responses at the "Strongly Agree" level of 7 out of 7. Both items measure whether or not pilots feel they receive enough information to fly in a fuel efficient manner. It seems incongruous to consider that perception of "enough information" to determine fuel efficiency will then lead to lower intention to save fuel. Therefore, we judge this hypothesis as **Inconclusive.**

Discussion:

Theoretical Contributions. Given the difficulty of obtaining behavioral measures, it is not surprising that much of the current TPB literature stops short of incorporating a PEB measurement. This study represents a unique opportunity to study a little-investigated population with a high per-capita influence over petroleum consumption. Although the relationship between INT and PEB seems small at -0.114, the figure is statistically significant ($p < 0.05$), and given the $4 billion USD used by USAF cargo aircraft in 2017, even small but predictable coefficients may indicate larger savings. In addition, cargo pilots by and large indicate they intend to save fuel while flying, with a culture favorable to fuel efficiency as a concept, and attitudes in favor of saving fuel. These results should not be interpreted to suggest pilots are averse to saving fuel.

Limitations and Future Studies. We call for future research into PEB where the behavior being measured and analyzed is the chief component of a professional duty. Few existing studies have attempted this, likely due in part to the difficulty of acquiring data at sufficient scale for a study. One such study, Gosnell et al. (2019), looked at 335 pilots from Virgin Atlantic, and was allowed to perform an intervention experiment. We were unable to perform an experiment, due to the constraints of working within the US military. Nevertheless, a major finding of this study – that Subjective Norm strongly influences pilots' intention to fly in an efficient manner – largely parallels a major finding of Gosnell et al. (2019), which indicated that attitudes and perceptions among groups of pilots influence the decision to conserve fuel while flying.

Another limitation of this study is the metric which does not fully isolate discretionary fuel consumption from non-discretionary fuel consumption. Such a metric, building on the research performed by Reiman (2014) and Schumacher (2015), would benefit future studies seeking to investigate pilots' influence on fuel consumption.

Practical Implications. We must ask: how can these results help us influence PEB in military pilots? How can these results help us predict or foster PEB? We would posit that, based on these results, the real-world constraints must be cleared from their behavioral path. The pilots indicate that they intend to save fuel, but the efficacy of their intentions will not matter if operational hurdles restrict their efforts. If leadership communicates a desire to conserve fuel, it must be matched by operational decisions which facilitate such fuel conservation. Anecdotal stories of a jet flying an entire sortie, largely empty but for one mission-capable (MICAP) part, are not uncommon, and serve to undermine the efforts taken by individual pilots to conserve fuel. A clear line of communication from pilots to command and scheduling operations is necessary to establish what works and what does not.

Influence on Subjective Norm. Once the operational hurdles have been surmounted, however, the clearest influence on pilots' INT towards saving fuel is their Subjective Norm. Pilots have reported feeling wearied by command attempting to influence SN with, as one pilot phrased it, "constantly pounding us over the head with fuel efficiency." Most pilots recognize that saving fuel is important, and with the tight-knit structure of a flying squadron, perceptions of social climate will strongly influence the pilots' desires to translate this drive into reality. Even with non-removable constraints such as operations tempo or the variability induced by diverts and weather, the INT to PEB link is statistically significant and merits further investigation.

Conclusion:

We examined USAF pilots' responses to a TPB questionnaire and compared the results with a fuel score derived from USAF historical records. We developed and tested a model based on the TPB literature proposing that instrumental and experiential attitudes, subjective norms, self-efficacy, and feedback serve as antecedents to intention, which in turn serves as an antecedent to behavior. We found support for many core tenets of TPB as reported in previous studies, such as the importance of self-efficacy and the significance of the intention-behavior relationship. However, our findings diverged from existing TPB research due to the outsize role that subjective norms played in determining intention. Subjective norms represent perceived social pressure, which could be a major factor in determining the intentions of individuals in settings with emphasis on camaraderie and group identity, such as USAF flying squadrons. Our findings indicate that while pilots can enact fuel savings through their intentions, it is imperative that change makers encourage such behavioral change with caution due to prior blunt-force efforts "poisoning the well" so to speak. USAF pilots, in general, indicate they intend to save fuel but feel boxed in with pressure to save fuel on one side and poor operational practices on the other. Saving fuel in an organization as large as the USAF is imperative and can be fostered by listening to the experiences of our cargo pilots.

V. Discussion and Conclusions

Results from the MASEM analysis indicate support for the core TPB relationship where pro-environmental behavior is primarily driven by intent, which in turn is driven by attitudes. As the literature has indicated, a distinction should be drawn between specific and nonspecific behaviors. Exactly where to draw that line is a matter of judgment on the part of the researcher, but the purpose of such a distinction is highlighted by Kaiser and Gutscher (2003), which demonstrates that the predictive capability of PBC upon BEH is stronger with specific behaviors and weaker with nonspecific behaviors. The behaviors studied in the MASEM research were sufficiently specific to provoke a noticeable relationship between PBC and BEH, but this relationship is weak and the benefit of including it is largely for model fit indices.

In studying both civilian automotive drivers and USAF cargo pilots, the strength of the metric of evaluation was critical. The key limitation of the automotive study and the aircraft study alike was the measure of pro-environmental behavior. The automotive study PEB measure was constrained by the means of data acquisition, due to its self-reported nature. Such self-reported metrics are less preferable to use than objectively collected behavioral data. The difficulty of obtaining objective behavioral data is hinted at by the share of studies collected for the MASEM which used self-reported data.

The behavioral metric in the aircraft study was objective, being drawn from historical USAF fuel consumption and adjusted for a major source of non-discretionary fuel consumption. The limitations of this metric highlight the need for building upon AFIT's existing research and further isolate the discretionary component of fuel consumption.

Appendices

Appendix A: Two-Stage Structural Equation Modeling Output (TSSEM), (Paper I)

```
R Console Page 1
R version 3.6.1 (2019-07-05) -- "Action of the Toes"
Copyright (C) 2019 The R Foundation for Statistical Computing
Platform: x86_64-w64-mingw32/x64 (64-bit)
R is free software and comes with ABSOLUTELY NO WARRANTY.
You are welcome to redistribute it under certain conditions.
Type 'license()' or 'licence()' for distribution details.
Natural language support but running in an English locale
R is a collaborative project with many contributors.
Type 'contributors()' for more information and
'citation()' on how to cite R or R packages in publications.
Type 'demo()' for some demos, 'help()' for on-line help, or
'help.start()' for an HTML browser interface to help.
Type 'q()' to quit R.
> local({pkg <- select.list(sort(.packages(all.available =
TRUE)),graphics=TRUE)
+ if(nchar(pkg)) library(pkg, character.only=TRUE)})
Loading required package: OpenMx
Notice: R GUI cannot display verbose output from the OpenMx backend. If
you need detail diagnostics then R CMD BATCH is one option.
"SLSQP" is set as the default optimizer in OpenMx.
mxOption(NULL, "Gradient algorithm") is set at "central".
mxOption(NULL, "Optimality tolerance") is set at "6.3e-14".
mxOption(NULL, "Gradient iterations") is set at "2".
> setwd ("C:\\Users\\Jamie\\Documents\\AFIT\\PhD\\2. MASEM\\MASEM Data
Analysis\\12 Dec 2019")
> setwd ("C:\\Users\\Jamie\\Documents\\AFIT\\PhD\\2. MASEM\\MASEM Data
Analysis")
> my.df5<-readLowTriMat("cottonfull10ormore.txt", no.var=5)
Read 945 items
> my.df5<-lapply(my.df5, function(x)
+ (dimnames(x) <- list(c("BEH", "INT", "ATT", "PBC", "SN"),
+ c("BEH", "INT", "ATT", "PBC", "SN"))
+ x})
Error: unexpected symbol in:
"c("BEH", "INT", "ATT", "PBC", "SN"))
x"
> my.df5<-lapply(my.df5, function(x)
+ {dimnames(x) <- list(c("BEH", "INT", "ATT", "PBC", "SN"),
+ c("BEH", "INT", "ATT", "PBC", "SN"))
+ x})
> my.n5<-c(250, 1335, 890, 190, 239, 198, 517, 437, 175, 68, 150, 186,
1810, 578, 620, 620, 620,
1275, 1275, 1275, 300, 452, 452, 595, 229, 229, 1340, 1340, 1340, 617,
200, 169, 169, 545, 392, 3
92, 392, 827, 827, 600, 425, 395, 419, 419, 419, 419, 595, 6602, 181,
161, 225, 259, 248, 180, 47
2, 1070, 1109, 180, 442, 331, 331, 194, 116)
> ##First Stage TSSEM Analysis
```

```
> random1<-tssem1(my.df5, my.n5, method="REM", RE.type="Diag")
> ##Rerun to remove error code
> random1<-rerun(random1, silent=TRUE)
Beginning initial fit attempt[ 0] MxComputeNumericDeriv 40/210[ 0]
MxComputeNumericDeriv 159/210
F it attempt 0, fit=-167.350550278782, new current best! (was
-167.350550278782)
Solution found! Final fit=-167.35055 (started at -167.35055) (1
attempt(s): 1 valid, 0 errors)
> summary(random1)
Call:
meta(y = ES, v = acovR, RE.constraints = Diag(paste0(RE.startvalues,
"*Tau2_", 1:no.es, "_", 1:no.es)), RE.lbound = RE.lbound,
I2 = I2, model.name = model.name, suppressWarnings = TRUE,
silent = silent, run = run)
95% confidence intervals: z statistic approximation
Coefficients:
Estimate Std.Error lbound ubound z value Pr(>|z|)
Intercept1 0.5163664 0.0424371 0.4331913 0.5995415 12.1678 < 2.2e-16
***
Intercept2 0.3434833 0.0284435 0.2877351 0.3992315 12.0760 < 2.2e-16
***
R Console Page 2
Intercept3 0.3224204 0.0362837 0.2513055 0.3935352 8.8861 < 2.2e-16 ***
Intercept4 0.2465818 0.0362160 0.1755998 0.3175638 6.8086 9.852e-12 ***
Intercept5 0.5028192 0.0200291 0.4635627 0.5420756 25.1044 < 2.2e-16
***
Intercept6 0.4242850 0.0270132 0.3713401 0.4772299 15.7066 < 2.2e-16
***
Intercept7 0.4234633 0.0280900 0.3684079 0.4785187 15.0752 < 2.2e-16
***
Intercept8 0.3506744 0.0244452 0.3027628 0.3985861 14.3453 < 2.2e-16
***
Intercept9 0.3981754 0.0232840 0.3525396 0.4438112 17.1008 < 2.2e-16
***
Intercept10 0.2975732 0.0256076 0.2473831 0.3477632 11.6205 < 2.2e-16
***
Tau2_1_1 0.0680727 0.0158458 0.0370155 0.0991299 4.2959 1.739e-05 ***
Tau2_2_2 0.0324218 0.0074461 0.0178278 0.0470158 4.3542 1.335e-05 ***
Tau2_3_3 0.0538935 0.0120864 0.0302045 0.0775825 4.4590 8.234e-06 ***
Tau2_4_4 0.0499084 0.0116174 0.0271387 0.0726781 4.2960 1.739e-05 ***
Tau2_5_5 0.0223120 0.0043715 0.0137440 0.0308800 5.1039 3.327e-07 ***
Tau2_6_6 0.0413118 0.0078933 0.0258411 0.0567824 5.2338 1.661e-07 ***
Tau2_7_7 0.0429489 0.0083467 0.0265897 0.0593081 5.1456 2.666e-07 ***
Tau2_8_8 0.0350983 0.0066657 0.0220338 0.0481629 5.2655 1.398e-07 ***
Tau2_9_9 0.0305935 0.0059376 0.0189560 0.0422309 5.1525 2.570e-07 ***
Tau2_10_10 0.0367825 0.0071929 0.0226847 0.0508803 5.1137 3.159e-07 ***
---
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Q statistic on the homogeneity of effect sizes: 16273.5
Degrees of freedom of the Q statistic: 515
P value of the Q statistic: 0
Heterogeneity indices (based on the estimated Tau2):
Estimate
Intercept1: I2 (Q statistic) 0.9824
```

```
Intercept2: I2 (Q statistic) 0.9599
Intercept3: I2 (Q statistic) 0.9723
Intercept4: I2 (Q statistic) 0.9709
Intercept5: I2 (Q statistic) 0.9591
Intercept6: I2 (Q statistic) 0.9688
Intercept7: I2 (Q statistic) 0.9749
Intercept8: I2 (Q statistic) 0.9611
Intercept9: I2 (Q statistic) 0.9655
Intercept10: I2 (Q statistic) 0.9620
Number of studies (or clusters): 63
Number of observed statistics: 525
Number of estimated parameters: 20
Degrees of freedom: 505
-2 log likelihood: -167.3506
OpenMx status1: 0 ("0" or "1": The optimization is considered fine.
Other values may indicate problems.)
> ##Second Stage of TSSEM, create A and S matrices based on desired
models
> ##Model 1, TPB with no correlations between constructs
> ##Model 1, A Matrix
> A1<-create.mxMatrix(c(0, 0, 0, 0, 0, "0.1*I2B", 0, 0, 0, 0, 0,
"0.1*A2I", 0, 0, 0, 0, "0.1*P2I"
, 0, 0, 0, 0, "0.1*S2I", 0, 0, 0), type="Full", nrow=5, ncol=5,
byrow=TRUE)
> A1
FullMatrix 'untitled1'
$labels
[,1] [,2] [,3] [,4] [,5]
[1,] NA NA NA NA NA
[2,] "I2B" NA NA NA NA
[3,] NA "A2I" NA NA NA
[4,] NA "P2I" NA NA NA
[5,] NA "S2I" NA NA NA
$values
[,1] [,2] [,3] [,4] [,5]
[1,] 0.0 0.0 0 0 0
[2,] 0.1 0.0 0 0 0
[3,] 0.0 0.1 0 0 0
[4,] 0.0 0.1 0 0 0
[5,] 0.0 0.1 0 0 0
$free
R Console Page 3
[,1] [,2] [,3] [,4] [,5]
[1,] FALSE FALSE FALSE FALSE FALSE
[2,] TRUE FALSE FALSE FALSE FALSE
[3,] FALSE TRUE FALSE FALSE FALSE
[4,] FALSE TRUE FALSE FALSE FALSE
[5,] FALSE TRUE FALSE FALSE FALSE
$lbound: No lower bounds assigned.
$ubound: No upper bounds assigned.
> S1<-create.mxMatrix(c("0.1*ErrVarB", 0, 0, 0, 0, 0, "0.1*ErrVarI", 0,
0, 0, 0, 0, 1, 0, 0, 0, 0
, 0, 1, 0, 0, 0, 0, 0, 1), type="Full", nrow=5, ncol=5, byrow=TRUE)
> S1
FullMatrix 'untitled1'
```

```
$labels
[,1] [,2] [,3] [,4] [,5]
[1,] "ErrVarB" NA NA NA NA
[2,] NA "ErrVarI" NA NA NA
[3,] NA NA NA NA NA
[4,] NA NA NA NA NA
[5,] NA NA NA NA NA
$values
[,1] [,2] [,3] [,4] [,5]
[1,] 0.1 0.0 0 0 0
[2,] 0.0 0.1 0 0 0
[3,] 0.0 0.0 1 0 0
[4,] 0.0 0.0 0 1 0
[5,] 0.0 0.0 0 0 1
$free
[,1] [,2] [,3] [,4] [,5]
[1,] TRUE FALSE FALSE FALSE FALSE
[2,] FALSE TRUE FALSE FALSE FALSE
[3,] FALSE FALSE FALSE FALSE FALSE
[4,] FALSE FALSE FALSE FALSE FALSE
[5,] FALSE FALSE FALSE FALSE FALSE
$lbound: No lower bounds assigned.
$ubound: No upper bounds assigned.
> ##Now we've created our A and S matrices for Model 1 (named A1 and
S1)
> ##Let's create matrices for Model 2. Fortunately, since the paths
between constructs are the same, we can just use A1.
> ##We do need to make an S2 matrix though, as now we have correlations
between independent constructs.
> ##Fortunately, S2 will be our S matrix through models 2, 3, and 4.
Nice!
> S2<-create.mxMatrix(c("0.1*ErrVarB", 0, 0, 0, 0, 0, "0.1*ErrVarI", 0,
0, 0, 0, 0, 1, 0, 0, 0, 0
, "0.1*CorrPA", 1, 0, 0, 0, "0.1*CorrSA", "0.1*CorrSP", 1),
type="Full", nrow=5, ncol=5, byrow=TR
UE)
> S2
FullMatrix 'untitled1'
$labels
[,1] [,2] [,3] [,4] [,5]
[1,] "ErrVarB" NA NA NA NA
[2,] NA "ErrVarI" NA NA NA
[3,] NA NA NA NA NA
[4,] NA NA "CorrPA" NA NA
[5,] NA NA "CorrSA" "CorrSP" NA
$values
[,1] [,2] [,3] [,4] [,5]
[1,] 0.1 0.0 0.0 0.0 0
[2,] 0.0 0.1 0.0 0.0 0
[3,] 0.0 0.0 1.0 0.0 0
[4,] 0.0 0.0 0.1 1.0 0
R Console Page 4
[5,] 0.0 0.0 0.1 0.1 1
$free
[,1] [,2] [,3] [,4] [,5]
```

```
[1,] TRUE FALSE FALSE FALSE FALSE
[2,] FALSE TRUE FALSE FALSE FALSE
[3,] FALSE FALSE FALSE FALSE FALSE
[4,] FALSE FALSE TRUE FALSE FALSE
[5,] FALSE FALSE TRUE TRUE FALSE
$lbound: No lower bounds assigned.
$ubound: No upper bounds assigned.
> ##Create A3, A-matrix for Model 3
> A3<-create.mxMatrix(c(0, 0, 0, 0, 0, "0.1*I2B", 0, 0, 0, 0, 0,
"0.1*A2I", 0, 0, 0, "0.1*P2B", "
0.1*P2I", 0, 0, 0, 0, "0.1*S2I", 0, 0, 0), type="Full", nrow=5, ncol=5,
byrow=TRUE)
> A3
FullMatrix 'untitled1'
$labels
[,1] [,2] [,3] [,4] [,5]
[1,] NA NA NA NA NA
[2,] "I2B" NA NA NA NA
[3,] NA "A2I" NA NA NA
[4,] "P2B" "P2I" NA NA NA
[5,] NA "S2I" NA NA NA
$values
[,1] [,2] [,3] [,4] [,5]
[1,] 0.0 0.0 0 0 0
[2,] 0.1 0.0 0 0 0
[3,] 0.0 0.1 0 0 0
[4,] 0.1 0.1 0 0 0
[5,] 0.0 0.1 0 0 0
$free
[,1] [,2] [,3] [,4] [,5]
[1,] FALSE FALSE FALSE FALSE FALSE
[2,] TRUE FALSE FALSE FALSE FALSE
[3,] FALSE TRUE FALSE FALSE FALSE
[4,] TRUE TRUE FALSE FALSE FALSE
[5,] FALSE TRUE FALSE FALSE FALSE
$lbound: No lower bounds assigned.
$ubound: No upper bounds assigned.
> ##Create A4, A-matrix for Model 4
> A4<-create.mxMatrix(c(0, 0, 0, 0, 0, "0.1*I2B", 0, 0, 0, 0,
"0.1*A2B", "0.1*A2I", 0, 0, 0, "0.1
*P2B", "0.1*P2I", 0, 0, 0, "0.1*S2B", "0.1*S2I", 0, 0, 0), type="Full",
nrow=5, ncol=5, byrow=TRU
E)
> A4
FullMatrix 'untitled1'
$labels
[,1] [,2] [,3] [,4] [,5]
[1,] NA NA NA NA NA
[2,] "I2B" NA NA NA NA
[3,] "A2B" "A2I" NA NA NA
[4,] "P2B" "P2I" NA NA NA
[5,] "S2B" "S2I" NA NA NA
$values
[,1] [,2] [,3] [,4] [,5]
[1,] 0.0 0.0 0 0 0
```

```
[2,] 0.1 0.0 0 0 0
[3,] 0.1 0.1 0 0 0
[4,] 0.1 0.1 0 0 0
[5,] 0.1 0.1 0 0 0
R Console Page 5
$free
[,1] [,2] [,3] [,4] [,5]
[1,] FALSE FALSE FALSE FALSE FALSE
[2,] TRUE FALSE FALSE FALSE FALSE
[3,] TRUE TRUE FALSE FALSE FALSE
[4,] TRUE TRUE FALSE FALSE FALSE
[5,] TRUE TRUE FALSE FALSE FALSE
$lbound: No lower bounds assigned.
$ubound: No upper bounds assigned.
> ##All A matrices and S matrices constructed. Let's run the second
stage analysis.
> ##Run Model 1 (A1, S1)
> summary(tssem2(random1, Amatrix=A1, Smatrix=S1, intervals.type="LB",
diag.constraints=TRUE))
Call:
wls(Cov = pooledS, aCov = aCov, n = tssem1.obj$total.n, Amatrix =
Amatrix,
Smatrix = Smatrix, Fmatrix = Fmatrix, diag.constraints =
diag.constraints,
cor.analysis = cor.analysis, intervals.type = intervals.type,
mx.algebras = mx.algebras, model.name = model.name, suppressWarnings =
suppressWarnings,
silent = silent, run = run)
95% confidence intervals: Likelihood-based statistic
Coefficients:
Estimate Std.Error lbound ubound z value Pr(>|z|)
I2B 0.55413 NA 0.49910 0.60957 NA NA
A2I 0.57145 NA 0.53872 0.60433 NA NA
P2I 0.50272 NA 0.46268 0.54296 NA NA
S2I 0.51833 NA 0.47791 0.55898 NA NA
ErrVarB 1.00000 NA 1.00000 1.00000 NA NA
ErrVarI 0.69294 NA 0.62839 0.75089 NA NA
Goodness-of-fit indices:
Value
Sample size 39307.0000
Chi-square of target model 65.2522
DF of target model 6.0000
p value of target model 0.0000
Number of constraints imposed on "Smatrix" 2.0000
DF manually adjusted 0.0000
Chi-square of independence model 1981.8366
DF of independence model 10.0000
RMSEA 0.0159
RMSEA lower 95% CI 0.0125
RMSEA upper 95% CI 0.0194
SRMR 0.0643
TLI 0.9499
CFI 0.9700
AIC 53.2522
BIC 1.7772
```

```
OpenMx status1: 0 ("0" or "1": The optimization is considered fine.
Other values indicate problems.)
Warning messages:
1: In checkRAM(Amatrix = Amatrix, Smatrix = Smatrix, cor.analysis =
cor.analysis) :
The variances of the independent variables in 'Smatrix' must be fixed
at 1.
2: In checkRAM(Amatrix = Amatrix, Smatrix = Smatrix, cor.analysis =
cor.analysis) :
The variances of the dependent variables in 'Smatrix' should be free.
> ##Run Model 2 (A1, S2)
> summary(tssem2(random1, Amatrix=A1, Smatrix=S2, intervals.type="LB",
diag.constraints=TRUE))
Call:
wls(Cov = pooledS, aCov = aCov, n = tssem1.obj$total.n, Amatrix =
Amatrix,
Smatrix = Smatrix, Fmatrix = Fmatrix, diag.constraints =
diag.constraints,
cor.analysis = cor.analysis, intervals.type = intervals.type,
mx.algebras = mx.algebras, model.name = model.name, suppressWarnings =
suppressWarnings,
silent = silent, run = run)
95% confidence intervals: Likelihood-based statistic
R Console Page 6
Coefficients:
Estimate Std.Error lbound ubound z value Pr(>|z|)
I2B 0.593402 NA 0.533660 0.653872 NA NA
A2I 0.514185 NA 0.477329 0.551177 NA NA
P2I 0.443532 NA 0.394663 0.492559 NA NA
S2I 0.422202 NA 0.371594 0.473031 NA NA
ErrVarB 1.000000 NA 1.000000 1.000000 NA NA
ErrVarI 0.647874 NA 0.572451 0.715207 NA NA
CorrPA 0.122710 NA 0.066545 0.178376 NA NA
CorrSA 0.181251 NA 0.126552 0.235389 NA NA
CorrSP 0.110482 NA 0.051861 0.168407 NA NA
Goodness-of-fit indices:
Value
Sample size 39307.0000
Chi-square of target model 8.7642
DF of target model 3.0000
p value of target model 0.0326
Number of constraints imposed on "Smatrix" 2.0000
DF manually adjusted 0.0000
Chi-square of independence model 1981.8366
DF of independence model 10.0000
RMSEA 0.0070
RMSEA lower 95% CI 0.0018
RMSEA upper 95% CI 0.0126
SRMR 0.0338
TLI 0.9903
CFI 0.9971
AIC 2.7642
BIC -22.9732
OpenMx status1: 0 ("0" or "1": The optimization is considered fine.
Other values indicate problems.)
```

```
Warning messages:
1: In checkRAM(Amatrix = Amatrix, Smatrix = Smatrix, cor.analysis =
cor.analysis) :
The free parameters of the 'Smatrix' must be symmetric.
2: In checkRAM(Amatrix = Amatrix, Smatrix = Smatrix, cor.analysis =
cor.analysis) :
The labels of 'Smatrix' must be symmetric.
3: In checkRAM(Amatrix = Amatrix, Smatrix = Smatrix, cor.analysis =
cor.analysis) :
The values of 'Smatrix' must be symmetric.
4: In checkRAM(Amatrix = Amatrix, Smatrix = Smatrix, cor.analysis =
cor.analysis) :
The variances of the independent variables in 'Smatrix' must be fixed
at 1.
5: In checkRAM(Amatrix = Amatrix, Smatrix = Smatrix, cor.analysis =
cor.analysis) :
The variances of the dependent variables in 'Smatrix' should be free.
> ##Run Model 3 (A3, S2)
> summary(tssem2(random1, Amatrix=A3, Smatrix=S2, intervals.type="LB",
diag.constraints=TRUE))
Call:
wls(Cov = pooledS, aCov = aCov, n = tssem1.obj$total.n, Amatrix =
Amatrix, Smatrix = Smatrix, Fmatrix = Fmatrix, diag.constraints =
diag.constraints,
cor.analysis = cor.analysis, intervals.type = intervals.type,
mx.algebras = mx.algebras, model.name = model.name, suppressWarnings =
suppressWarnings,
silent = silent, run = run)
95% confidence intervals: Likelihood-based statistic
Coefficients:
Estimate Std.Error lbound ubound z value Pr(>|z|)
I2B 0.5728442 NA 0.5095269 0.6368516 NA NA
A2I 0.5163072 NA 0.4792798 0.5534739 NA NA
P2B 0.1176763 NA -0.0039198 0.2327423 NA NA
P2I 0.3570337 NA 0.2580215 0.4584600 NA NA
S2I 0.4246491 NA 0.3737333 0.4757826 NA NA
ErrVarB 1.0000000 NA 1.0000000 1.0000000 NA NA
ErrVarI 0.6718495 NA 0.5944203 0.7403825 NA NA
CorrPA 0.1315979 NA 0.0747432 0.1879576 NA NA
CorrSA 0.1790607 NA 0.1241777 0.2333615 NA NA
CorrSP 0.1173899 NA 0.0585308 0.1755164 NA NA
R Console Page 7
Goodness-of-fit indices:
Value
Sample size 39307.0000
Chi-square of target model 5.1565
DF of target model 2.0000
p value of target model 0.0759
Number of constraints imposed on "Smatrix" 2.0000
DF manually adjusted 0.0000
Chi-square of independence model 1981.8366
DF of independence model 10.0000
RMSEA 0.0063
RMSEA lower 95% CI 0.0000
RMSEA upper 95% CI 0.0133
```

```
SRMR 0.0238
TLI 0.9920
CFI 0.9984
AIC 1.1565
BIC -16.0018
OpenMx status1: 0 ("0" or "1": The optimization is considered fine.
Other values indicate problems.)
Warning messages:
1: In checkRAM(Amatrix = Amatrix, Smatrix = Smatrix, cor.analysis =
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The free parameters of the 'Smatrix' must be symmetric.
2: In checkRAM(Amatrix = Amatrix, Smatrix = Smatrix, cor.analysis =
cor.analysis) :
The labels of 'Smatrix' must be symmetric.
3: In checkRAM(Amatrix = Amatrix, Smatrix = Smatrix, cor.analysis =
cor.analysis) :
The values of 'Smatrix' must be symmetric.
4: In checkRAM(Amatrix = Amatrix, Smatrix = Smatrix, cor.analysis =
cor.analysis) :
The variances of the independent variables in 'Smatrix' must be fixed
at 1.
5: In checkRAM(Amatrix = Amatrix, Smatrix = Smatrix, cor.analysis =
cor.analysis) :
The variances of the dependent variables in 'Smatrix' should be free.
> ##Run Model 4 (A4, S2)
> summary(tssem2(random1, Amatrix=A4, Smatrix=S2, intervals.type="LB",
diag.constraints=TRUE))
Call:
wls(Cov = pooledS, aCov = aCov, n = tssem1.obj$total.n, Amatrix =
Amatrix,
Smatrix = Smatrix, Fmatrix = Fmatrix, diag.constraints =
diag.constraints,
cor.analysis = cor.analysis, intervals.type = intervals.type,
mx.algebras = mx.algebras, model.name = model.name, suppressWarnings =
suppressWarnings,
silent = silent, run = run)
95% confidence intervals: Likelihood-based statistic
Coefficients:
Estimate Std.Error lbound ubound z value Pr(>|z|)
I2B 0.516366 NA 0.433191 0.599541 NA NA
A2B 0.114328 NA 0.016863 0.200782 NA NA
A2I 0.443784 NA 0.377918 0.514685 NA NA
P2B 0.140904 NA 0.027779 0.245662 NA NA
P2I 0.351527 NA 0.263659 0.441133 NA NA
S2B 0.038070 NA -0.081271 0.145622 NA NA
S2I 0.403805 NA 0.314027 0.500521 NA NA
ErrVarB 1.000000 NA 1.000000 1.000000 NA NA
ErrVarI 0.733366 NA 0.640551 0.812345 NA NA
CorrPA 0.125522 NA 0.069056 0.181450 NA NA
CorrSA 0.182058 NA 0.127297 0.236234 NA NA
CorrSP 0.113970 NA 0.055127 0.172167 NA NA
Goodness-of-fit indices:
Value
Sample size 39307.0
Chi-square of target model 0.0
```

```
DF of target model 0.0
p value of target model 0.0
Number of constraints imposed on "Smatrix" 2.0
DF manually adjusted 0.0
Chi-square of independence model 1981.8
DF of independence model 10.0
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RMSEA 0.0
RMSEA lower 95% CI 0.0
RMSEA upper 95% CI 0.0
SRMR 0.0
TLI -Inf
CFI 1.0
AIC 0.0
BIC 0.0
OpenMx status1: 0 ("0" or "1": The optimization is considered fine.
Other values indicate problems.)
Warning messages:
1: In checkRAM(Amatrix = Amatrix, Smatrix = Smatrix, cor.analysis =
cor.analysis) :
The free parameters of the 'Smatrix' must be symmetric.
2: In checkRAM(Amatrix = Amatrix, Smatrix = Smatrix, cor.analysis =
cor.analysis) :
The labels of 'Smatrix' must be symmetric.
3: In checkRAM(Amatrix = Amatrix, Smatrix = Smatrix, cor.analysis =
cor.analysis) :
The values of 'Smatrix' must be symmetric.
4: In checkRAM(Amatrix = Amatrix, Smatrix = Smatrix, cor.analysis =
cor.analysis) :
The variances of the independent variables in 'Smatrix' must be fixed
at 1.
5: In checkRAM(Amatrix = Amatrix, Smatrix = Smatrix, cor.analysis =
cor.analysis) :
The variances of the dependent variables in 'Smatrix' should be free.
> save.image("C:\\Users\\Jamie\\Documents\\AFIT\\PhD\\2. MASEM\\MASEM
Data Analysis\\20191212 Cotton MASEM 40 Studies 63 Matrices.RData")
>
```

Appendix B: Exploratory Factor Analysis Results (Paper II)

	Constructs						
Item	1	2	3	4	5	6	7
TPBAtt1_1	.069	.880	.026	.060	-.026	.146	.052
TPBAtt1_2r	.054	.815	.040	.117	.052	-.017	-.006
TPBAtt1_3	.059	.878	.001	.070	.006	.196	-.011
TPBAtt1_4	.057	.840	.035	.119	-.010	.166	-.042
TPBAtt1_5r	.136	.714	.150	.080	.047	-.030	.043
TPBAtt2_1	.188	.105	.078	.628	.085	.381	-.166
TPBAtt2_2	.142	.069	.023	.853	-.032	.037	.105
TPBAtt2_3r	.022	.102	.123	.800	.046	-.033	.275
TPBAtt2_4r**	.044	.031	.288	.569	-.013	-.202	.288
TPBAtt2_5	.018	.228	.180	.789	.100	.170	.009
TPBSubjNorm_1	.207	-.087	.727	.176	.025	-.116	-.095
TPBSubjNorm_2	.137	.027	.666	.061	.090	.093	-.069
TPBSubjNorm_3	-.070	-.131	.601	.021	-.054	-.217	.154
TPBSubjNorm_4	.161	-.089	.728	.245	.031	-.092	-.083
TPBSubjNorm_5**	.005	.328	.547	-.034	.047	.158	-.034
TPBSubjNorm_6	-.131	.296	.643	-.077	.040	.070	.044
TPBSubjNorm_7**	.199	.067	.555	.180	-.014	.195	-.095
TPBPBC1_1	.690	.023	.156	.019	.174	.165	.067
TPBPBC1_2	.636	.053	.118	.031	.361	-.097	.011
TPBPBC1_3**	.585	.040	.205	.085	.360	-.098	.058
TPBPBC1_4	.833	.070	-.075	.117	.053	-.012	.000
TPBPBC1_5	.779	.117	.091	.050	.110	.024	.116
TPBPBC1_6	.659	.080	.085	.099	.091	.105	.158
TPBPBC1_7	.667	.048	.177	.006	.336	.020	.112
TPBPBC1_8r	.003	.117	.048	.170	.152	.731	.121
TPBPBC1_9r	.255	.176	-.048	.177	-.159	.663	-.019

TPBPBC1_10r	-.111	.121	.108	-.149	-.071	.698	.175
TPBPBC2_1r	.326	.080	-.067	.081	.115	.229	.714
TPBPBC2_2r	.195	-.050	-.014	.037	.154	.107	.701
TPBPBC2_3r	-.010	.012	-.107	.271	-.076	-.017	.668
TPBPBC2_4**	.193	.143	.413	.059	.168	.131	-.002
TPBFeedback_1	.385	.004	.148	.085	.800	.022	.100
TPBFeedback_2	.329	.072	.040	.023	.847	-.013	.037
TPBFeedback_3	.320	-.020	.006	.018	.807	-.011	.045

**** = removed due to low factor loadings**

	Constructs		
Item	**1**	**2**	**3**
driveEff_1	.078	.624	-.027
driveEff_2	.083	.628	-.246
driveEff_3	.138	.609	-.023
driveEff_4	.071	.673	-.028
driveEff_5	.334	.458	.189
driveEff_6	.165	.648	.219
driveEff_7	.113	.272	.665
driveEff_8	.068	.645	.307
driveEff_9	.112	.493	.515
driveEff_10	.037	-.083	.461
driveEff_11	.125	.662	.084
driveEff_12	.047	.508	.094
driveEff_13	.064	.042	.596
TPBIntention_1	.383	-.034	.294
TPBIntention_2	.759	.210	.178
TPBIntention_3	.798	.205	-.015
TPBIntention_4r	.553	.223	-.068

EFA Factor Loadings from Items upon Constructs (Dependents)

Appendix C: Survey Questionnaire for Automotive Drivers (Paper II)

Construct	Item	Question (1: Strongly Disagree/Not At All; 4: Neutral/No Opinion; 7: Strongly Agree/Always)
Attitudes Towards Saving Fuel (Att 1)	1	Saving fuel over my next dozen drives would be (bad/good)
	2r	“” (pleasant/unpleasant)
	3	“” (harmful/beneficial)
	4	“” (worthless/valuable)
Attitudes Towards Moderating Highway Speed (Att 2)	2	“” (is harmful/is beneficial)
	3r	“” (is good/is bad)
	4r	“” (is pleasant/is unpleasant)
	5	“” (is worthless/is useful)
Perceived Behavioral Control: Self-Efficacy over Fuel Consumption (PBC-SE)	1	I am confident that I could drive in a fuel-efficient manner if I wanted to.
	2	I find it easy to drive fuel efficiently.
	3	For me to achieve fuel-efficient driving standards is easy.
	4	I can directly improve my overall fuel efficiency while driving.
	5	As the driver, I can directly improve the overall fuel efficiency when I drive.
	6	I can change my driving to be more fuel efficient.
	7	I have enough flexibility to influence how fuel efficient the drive is.
Perceived Behavioral Control: Controllability over Fuel Consumption (PBC-C)	1r	The decision to drive in a fuel-efficient way is beyond my control.
	2r	Outside factors determine my fuel-efficiency more than my choices.
	3r	Whether or not I drive in a fuel-efficient way is not entirely up to me.
Subjective Norm (SN)	1	Most people who are important to me think that I should drive in a fuel efficient manner.
	2	It is expected that I do my day to day commuting fuel-efficiently.
	4	People who are important to me want me to be fuel efficient.
Intention	1	I expect to achieve higher MPG than my car was advertised to have.
	2	I prefer to drive in a fuel-efficient manner.
	3	I intend to be fuel-efficient when I drive.
	4r	I don’t think about fuel-efficiency before a trip.
Behavior (Eco-Driving Practices)	1	When driving, how often do you loosen pressure on the accelerator/gas pedal at traffic lights?
	2	When driving, how often do you loosen pressure on the accelerator/gas pedal when going downhill?
	3	When driving, how often do you remove pressure from the accelerator/gas pedal to avoid further braking?
	4	When driving, how often do you watch for vehicles ahead to reduce need for rapid deceleration/braking?
	5	When driving, how often do you avoid sudden braking while driving?
	6	When driving, how often do you maintain a constant distance behind the vehicles in front of me?
	7	When driving, how often do you anticipate road conditions to reduce need for rapid acceleration or deceleration?
	8	When driving, how often do you plan [your] route to reduce driving time?

Appendix D: List of Items Selected for Structural Modeling (Paper III)

INT2 I prefer to fly in a fuel-efficient manner.

INT3 I intend to be fuel-efficient when I fly.

*INT4 I do not think about fuel efficiency when I fly.

ATT1_IN1 Saving fuel over the next dozen missions would be (Bad/Good):

ATT1_IN3 Saving fuel over the next dozen missions would be (Harmful/Beneficial):

ATT1_IN4 Saving fuel over the next dozen missions would be (Worthless/Valuable):

ATT2_EX2: Flying at max range airspeed (i.e. the airspeed which achieves the best range, without sacrificing safety or timeliness) (Is Harmful/Is Beneficial)

ATT2_EX5: Flying at max range airspeed (i.e. the airspeed which achieves the best range, without sacrificing safety or timeliness) (Is Worthless/Is Useful)

SN1 Pilots I respect think I should fly in a fuel efficient manner.

SN2 It is expected that I fly routine missions fuel-efficiently.

SN4 People who are important to me want me to be fuel efficient.

SN7 What other pilots do to conserve fuel is important to me.

PBC1_SE3 As the aircraft commander, I can directly improve the overall fuel efficiency of my mission.

PBC1_SE4 I have enough flexibility to influence the fuel efficiency of my flights.

PBC3-FB2 I receive enough information to determine if I have flown a fuel-efficient sortie.

PBC3-FB3 The system regularly gives me enough information to know I've flown fuel-efficiently.

*Items marked with an asterisk are reverse coded.

Appendix E: Descriptive Statistics for Fuel Saving Records

Records per Pilot	Frequency	Mean	Standard deviation
Three or Fewer	19/62	2.11	0.79
Four to Seven	17/62	5.06	0.87
Eight to Ten	9/62	9.33	0.67
More than Ten	17/62	15.82	4.71

Appendix F: Significance of Path Coefficients (Paper III)

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	t Statistics (|O/STDEV|)	p Values
ATT1 -> INT	-0.220	-0.218	0.046	4.801	0.000
ATT2 -> INT	0.101	0.101	0.041	2.497	0.013
INT -> PEB	-0.114	-0.116	0.043	2.637	0.008
PBC1 -> INT	0.231	0.233	0.035	6.608	0.000
PBC3 -> INT	-0.162	-0.161	0.058	2.784	0.005
SN -> INT	0.671	0.671	0.049	13.676	0.000

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*denotes studies used in MASEM procedure

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