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The cross-cultural challenges of integrating personal norms into the Theory of Planned Behavior: A meta-analytic structural equation modeling (MASEM) approach

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Generalizations
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Environmental behavior
Structural equation modeling

A B S T R A C T

The Theory of Planned Behavior (TPB) is a highly influential framework for studying human action. Research applying the TPB often follows the assumption that the framework – originally developed in the U.S. – is universal and can be effectively applied across geographical and cultural boundaries. With the power of meta-analytic structural equation modeling (MASEM), we test the above assumption across Hofstede’s and GLOBE’s individualism-collectivism cultural dimensions. Specifically, we compare 3 variations of the TPB model that are evident in the literature. Our findings focus on the context of environmental behavior, and are based on 255 samples with 130,354 respondents from 50 countries. We show that adding personal norms to the TPB model in addition to subjective norms, the typically included dimension of the norm construct, moderately improves understanding of cross-cultural differences in environmental behavior.

1. Introduction

A meaningful change in people’s environmental behavior is needed to be able to address climate change, and this requires a better understanding of the reasons why many people are not behaving in an environmentally friendly manner (Gifford, Lacroix, & Chen, 2018; Stern, 2011). Many scholars have applied the Theory of Planned Behavior (TPB) to better understand this reality (e.g., Bamberg & Möser, 2007; Hines, Hungerford, & Tomera, 1987; Morren & Grinstein, 2016). The TPB is a theoretical framework that explains behavior based on three key motivational factors and intention (Ajzen, 2001). Specifically, behavior is influenced by behavioral intention, which is determined independently by (1) attitudes toward the behavior (global positive or negative evaluations about performing the target behavior), (2) norms in the context of a given behavior (i.e., subjective norms, or judgment of the opinions of others, such as family and friends), and (3) perceived behavioral control (PBC; which refers to perceptions regarding the ease or difficulty of performing the target behavior). A direct link between PBC and behavior has been added to the framework (Ajzen & Madden, 1986).

Among the frameworks used to explain behavior from an individual difference approach, the TPB framework is the most wide-spread, having been applied across many countries. Multiple studies highlight the role of the social context, and norms specifically, to explain the reluctance to adopt environmental behavior (e.g., Hübner & Kaiser, 2006; Klokner, 2013; Kollmuss & Agyeman, 2002). Indeed, one of the seven psychological factors for inaction identified by Gifford (2011) in the context of environmental behavior is social comparison with others. Research shows that the importance of the social influence on environmental consumption differs across countries (Clark, Springmann, Hill, & Tilman., 2019). Individuals from different countries differ in the relative weights they place on TPB factors such as attitudes and norms, and the weights of these predictors vary across behaviors (e.g., Ajzen, 2001; Bagozzi, Lee, & Van Loo, 2001; Trafimow & Finlay, 1996). Other studies found that norms – specifically subjective norms – affect intention stronger in collectivist cultures, while attitudes are more important in individualistic cultures (Abrams, Ando, & Hinkle, 1998; Conner & Heywood-Everett, 1998). Such cultural inconsistencies in the effect of TPB factors, and specifically in the role of norms, have been found across numerous contexts, such as environmental behavior (Morren &

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Armitage (2001), consumers’ purchasing behavior (Choi & Geistfeld, 2004), entrepreneurship (Krueger, Reilly, & Carsrud, 2000), and health (Hagger & Chatzisarantis, 2009).

In this research, our aims and contributions are twofold: exploring how (a) personal norms influence the decision to adopt environmental behavior (b) across cultures, by synthesizing 255 samples from 231 studies with 130,354 respondents, combining the strengths of meta-analytical methods and structural equation modeling (SEM). Although the classical TPB model has focused on one dimension of the norm construct – subjective norms – we study how integrating personal norms into the TPB model allows us to shed light on previous mixed findings. Personal norms play a key role in environmental behavior, as it is associated with an enhanced feeling of moral obligation (Onwezen, Antonides, & Bartels, 2013; Stern, 2000), and have the potential to contribute to a better understanding of the role of behavior across cultures (e.g., Udo, Bagchi, & Maity, 2016). We test 3 competing TPB models across cultures, comparing 50 countries to study the moderating role of a key cultural distinction: Individualism versus collectivism.

Most authors who have tested the TPB framework across a large number of studies through meta-analysis did not differentiate between the countries and cultures in which the studies were conducted (e.g., Armitage & Conner, 2001; Bamberg & Möser, 2007; Hagger & Chatzisarantis, 2009). To the best of our knowledge, only two studies have systematically examined the role of cross-cultural differences in relationships among TPB constructs (Kaiser, Schultz, Berenguer, Corral-Verdugo, & Tankha, 2008; Morren & Grinstein, 2016). Morren and Grinstein (2016) only studied the bivariate relationships within the model, disregarded the model paths - enabling it to more accurately capture prior aggregated findings, and excluded the role of personal norms. Exploring the model holistically enables us to test the role of personal norms within the model (Sheng, Kong, Cortina, & Hou, 2016). Additionally, Morren and Grinstein’s results are based on a median split which simplifies the comparison of collectivist and individualistic countries. Kaiser et al. (2008) have explored how anticipated guilt and embarrassment differently affects the intention among students across four countries that vary on individualism. They found that culture did not moderate this relationship but adding anticipated guilt did improve model fit. Finally, although Bamberg and Möser (2007) and Klöckner (2013) have explored across multiple studies how personal norms should be integrated into the classical TPB framework, no meta-analysis has tested cross-cultural differences in how personal norms play a role.

2. Theoretical framework

2.1. TPB and norms

Initially, the TPB framework focused on subjective norms defined as “the perceived social pressure to perform or not to perform a behavior” (Ajzen, 1991, p. 188). Specifically, Ajzen and Fishbein (1980) argue that people use information based on the subjective norms they perceive in their surroundings, along with attitudes and PBC, to arrive at their decisions through reasoned action (see Fig. 1). Subjective norms are found to be the weakest predictor of intention. Armitage and Conner (2001) find in their meta-analysis of more than 100 studies that intention is better explained by attitudes (R² = 49%) than subjective norms (R² = 34%). A possible explanation for the weak effect of subjective norms could be the multifaceted norm dimension. Norms contain both instrumental and experiential aspects (Ajzen & Driver, 1992; Crites, Fabrigar, & Petty, 1994), often described as injunctive and descriptive subjective norms to accentuate the difference between perceiving what others think one should do versus what others do (Cialdini, 2003; Heath & Gifford, 2002; Kashima, Gallais, & McCamish, 1993). Injunctive norms constitute the moral rules of the group, whereas descriptive norms inform behavior (Cialdini, 1991).

Next to the influence of their social surroundings, people can be motivated by their personal norms. Personal norms are the personal conviction that some behavior is inherently right or wrong (Terry & Hogg, 2000). Schwartz argues that personal norms are internalized feelings of moral obligation towards others and lead to prosocial behavior when activated (Schwartz, 1968). The Norm Activation Model (NAM) posits that personal norms directly influence behavior and need to be activated before they can influence behavior (Schwartz, 1977). Personal norms are activated by awareness of the consequences of the behavior, and ascription of responsibility (which is influenced by awareness of consequences). Following the NAM, the Value-Belief-Norm (VBN) framework posits that, when activated, personal norms can elicit environmental behavior directly without referring to an explicit behavioral intention (Stern, 2000). Importantly, a person’s willingness

![Fig. 1. The hypothetical models in which personal norms are integrated in the TPB model.](image)

Note. B stands for Behavior, BI for Behavioral Intention/Intention, ATT for Attitudes, PBC for Perceived Behavioral Control, SN for Subjective Norms and PN for Personal Norms.
to follow these personal norms is not based on social sanctions (such as with subjective norms) but on individual feelings of guilt (Bamberg, Hunecke, & Blöbaum, 2007; Onwezen et al., 2013).

A conflict may arise between what is morally right and what one may intend to do or what the people in one’s surroundings would like them to do (Manstead, 2000). When one’s subjective norms are opposed to one’s attitudes, Manstead (2000) argues that people will consult their moral compass. Indeed, Hübner and Kaiser (2006) found that moral norms become important when a conflict arises between attitudes and subjective norms. Then, people need moral norms to decide whether they follow their own values or choose to behave in a way others consider to be appropriate (Hübner & Kaiser, 2006). Such conflict will occur more often with behaviors with a moral component, or for which social expectations exist (such as environmental behavior; Manstead, 2000). We refer to moral norms as personal norms, as both describe internalized, individual norms, and are measured using similar questions.

2.2. Integrating personal norms into TPB

The role of norms within the TPB framework and how this role influences TPB modeling effectiveness is still not clear. Scholars applied multiple theoretical approaches using various methodologies—offering mixed findings. Most research tests the classical TPB model by including personal and subjective norms as separate variables in a multiple (stepwise) regression (e.g., Abrahamse, Steg, Gifford, & Vlek, 2009; Carrico, Fraser, & Bazuin, 2013; Chen & Tung, 2010; Cordano, Marshall, & Silverman, 2010; Davis, O’Callaghan, & Knox, 2009; Dean, Raats, & Shepherd, 2012; Gardner & Abraham, 2010; Heath & Gifford, 2002; Klockner & Matthes, 2004; Pakpour, Zeidi, Emamjomeh, Asefzadeh, & Pearson, 2014; Tonglet, Phillips, & Read, 2004; Wan, Shen, & Choi, 2017; White, Smith, Terry, Greenslade, & McKimmie, 2009). Some of these studies demonstrated that adding personal norms to the TPB framework improves predictability of altruistic behaviors (Arvola et al., 2008; Harland, Staats, & Wilke, 1999; Hübner & Kaiser, 2006; Pakpour et al., 2014; Thøgersen & Olander, 2006; White, Smith, Terry, Greenslade, & McKimmie, 2009). Most of them found a stronger or equally strong effect of personal norms on intention or behavior when compared with subjective norms (except for: Davis et al., 2009; Dean et al., 2012; Wan et al., 2017).

Some studies compared how personal and subjective norms impact intention and behavior when simultaneously included in the model. Ajzen (2005) treated personal norms as an extension of subjective norms and attitudes, but did not expect a strong relationship between personal norms and intention. However, multiple studies found that personal norms affect intention stronger than subjective norms (Han, 2015; Kaiser & Scheutheule, 2003; Liu, Sheng, Mundorf, Redding, & Ye, 2017; Lizin, Van Dael, & Van Passel, 2017; Ru, Wang, & Yan, 2018; Shen, Si, Yu, & Si, 2019; Wan, Shen, & Yu, 2014). Similarly, Klockner and Ohms (2009) showed that personal norms more strongly and directly affect both self-reported and observed behavior compared to subjective norms, and Poaksus (2015) and Li, Xu, Chen, and Menassa (2019) found that personal norms directly impact behavior. However, Wan et al. (2012) found that the effect of subjective norms and personal norms on intention is equally strong, others found that only personal norms affect intention (Gao, Wang, Li, & Li, 2017; Huang, Lings, Beason, & Chou, 2018; Ru et al., 2018; Wang, Lin, & Li, 2018; Yazdanpanah & Forouzani, 2015), and still others found that only subjective norms affect intention (Chen & Tung, 2014; Schaffner, Ohnmacht, Weibel, & Mahrer, 2017; Stancu, Haugaard, & Låhteenmäki, 2016). Further, subjective norms may indirectly affect intention via personal norms (Han & Hyun, 2017; Onwezen et al., 2013; Zhang, Geng, & Sun, 2017), and Klockner’s (2013) meta-analysis confirmed that personal norms and attitudes influence intention, and subjective norms influence intention directly and indirectly via personal norms (and do not influence other variables).

Other authors explored how personal norms relate to attitudes and PBC using a path model approach (e.g., with SEM). Kaiser (2006) found evidence for an indirect influence on intention via attitudes and Chan and Bishop (2013) showed that personal norms act as a substitute for attitudes. Similarly, Malek-Saeidi, Rezaei, and Ajili (2012) found that personal norms affect attitude towards organic farming while subjective norms do not. Considerable evidence showed that personal norms influence intention directly and indirectly via attitudes (Arvola et al., 2008; Formara, Pattitoni, Mura, & Strazzera, 2016; Sophia & Klockner, 2011; Zhang et al., 2017). With respect to PBC, Thøgersen and Olander (2006) found that personal norms influence behavior directly but also indirectly via PBC. Using a panel study, they demonstrated that behavior strengthens personal norms over time (Thøgersen & Olander, 2006). Peters, Gutscher, and Scholz (2011) found that personal norms— influenced by subjective norms— affect intention indirectly via PBC.

2.3. Hypothetical models

Based on the review above, we compare three models to the classical TPB model in which personal norms are not included (Classical TPB). First, we test the extended version of the classical TPB model in which personal norms influence behavioral intention, as do the other TPB variables. Klockner (2013) found that the effect of personal norms on behavior is mediated by intention in a meta-analysis across 5 studies integrating VBN and TPB. However, the NAM framework states that personal norms channel the influence of awareness, beliefs and efficacy on behavior, and directly affect behavior. Following Klockner (2013) and the NAM framework, we test whether personal norms influence behavior indirectly and directly (Model 2, labeled Extended TPB).

Second, another stream of research emphasized that the attitude construct is more complex than originally discussed and consists of cognitive and affective (and behavioral) components (e.g., Trafimow & Sheeran, 1998). Additionally, some scholars argued that only when people experience a conflict among subjective norms and attitudes (Hübner & Kaiser, 2006; Manstead, 2000) they will rely on personal norms to decide on specific behavior due to bounded rationality, i.e., people only consider additional information if the conflict arises. While Hübner and Kaiser (2006) were able to assess the conflict between attitudes and subjective norms at the individual level, we only have aggregated data. They found that personal norms correlate higher with attitudes in a situation of harmony (Hübner & Kaiser, 2006). This suggests that the influence of personal norms on intention is mediated by attitudes. To allow for these complexities, and following others, Kaiser (2006) and Thøgersen and Olander (2006), we allow the effect of personal norms on intention to be mediated by attitudes and PBC (Model 3, labeled Mediated TPB).

Third, based on the growing research that studies the link between subjective and personal norms, we propose another model. This model offers a viable explanation for the weak link of subjective norms on intention (Armitage and Conner, 2001). Specifically, subjective norms have been found to indirectly affect intention via personal norms (Han & Hyun, 2017; Klockner, 2013; Onwezen et al., 2013; Zhang et al., 2017). Thøgersen (2009) showed that personal norms are more strongly embedded in cognition relative to subjective norms, and mediate the effect of subjective norms on behavior. He argued that personal norms are more than introspected subjective norms, and actually mediate the effect of motivations and convictions. We thus allow subjective norms to directly influence personal norms, and only affect intention via personal norms (Model 4, labeled Normative influence TPB).

We expect Models 2, 3 and 4 to fit better than the classical TPB model (Model 1) due to including personal norms. Most likely, the difference in model fit is greatest for Models 3 and 4 in which the more complex relationships between personal norms, subjective norms, attitudes and intention are explored. This leads us to formulate the following hypothesis:

H1. Model 2 (Extended TPB), Model 3 (Mediated TPB), and Model 4
H3. Personal norms play a stronger role in individualistic than collectivistic countries.
larger effect sizes and smaller studies to have small effect sizes. Although this causes some asymmetry, these patterns do not raise concern for publication bias. Note that the y-axis shows the Fisher z transformed correlation coefficients and the x-axis shows the inverted standard error (\( \sqrt{1/N - 3} \), following Sterne & Egger, 2001).

Table 1
Pooled correlation matrix (using random effects model).

<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Behavior (B)</td>
<td>–</td>
<td>73</td>
<td>86</td>
<td>77</td>
<td>45</td>
<td>82</td>
</tr>
<tr>
<td>2. Behavioral Intention (BI)</td>
<td>0.507</td>
<td>–</td>
<td>171</td>
<td>159</td>
<td>81</td>
<td>159</td>
</tr>
<tr>
<td>3. Attitudes (ATT)</td>
<td>0.347</td>
<td>0.531</td>
<td>–</td>
<td>161</td>
<td>87</td>
<td>164</td>
</tr>
<tr>
<td>4. Perceived Behavioral Control (PBC)</td>
<td>0.369</td>
<td>0.454</td>
<td>0.384</td>
<td>–</td>
<td>76</td>
<td>156</td>
</tr>
<tr>
<td>5. Personal Norms (PN)</td>
<td>0.387</td>
<td>0.519</td>
<td>0.472</td>
<td>0.374</td>
<td>–</td>
<td>78</td>
</tr>
<tr>
<td>6. Subjective Norms (SN)</td>
<td>0.328</td>
<td>0.474</td>
<td>0.418</td>
<td>0.374</td>
<td>0.419</td>
<td>–</td>
</tr>
</tbody>
</table>

Note. The number of separate samples is reported in the upper diagonal matrix; the pooled effect sizes are reported in the lower diagonal matrix.

3.2. Measures

TPB variables: We have carefully selected studies that include the original TPB variables (Ajzen & Fishbein, 1980). Some studies have included measures that were formulated similarly to the original TPB variables. PBC included items such as: “I am able to control whether I make most of my journeys in Brighton and Hove next week without using a car” (Gardner & Abraham, 2010); “If I wanted to, I would not have problems in succeeding to recycle E-waste” (Kumar, 2019). Alternative formulations used to measure self-efficacy: “Every little contribution from consumers helps to reduce the use of pesticides and artificial fertilizers in agriculture” (Thogersen & Ölander, 2006), or perceived consumer effectiveness: “I feel capable of helping solve the environmental problems” (Jaiswal & Kant, 2018) were also included as PBC. We excluded PBC measures if they only measured the absence of trust in behaviors: “There is not much that I can do about the environment” (Alzubaidi, Slade, & Dwivedi, 2020). In general, the items used to measure PBC or related concepts reflected the belief that an individual can do much about the environment. Similarly, attitudes were most often measured using the original TPB formulation: “Adopting energy efficiency practices is a smart measure” (Lopes, de Araújo Kalid, 2020).
Rodríguez, & Ávila Filho, 2019); “Purchasing green is a good idea” (Paul, Modi, & Patel, 2016). In some cases, measures that treated a general feeling about the behavior were included as attitudes: “The presence of green in the city makes us feel more alive” (Wan, Shen, & Choi, 2018); “Turning my PC off whenever I leave my desk is worthwhile” (Greaves et al., 2013). Behavior was measured using questions about what actually happened: “I usually separate all recyclable materials” (Liao & Li, 2019); or as an acceptance of behaviors: “It is acceptable for the hotel I am staying at to inform me of the reuse of towels and bath towels” (Bashir, Khwaja, Turi, & Toheed, 2019). If behavior was measured across multiple waves, we only reported the first wave. Norms: During our data collection we paid special attention to the norms. Most authors operationalized subjective norms as injunctive norms (e.g., De Leeuw, Valois, Ajzen, & Schmidt, 2015; Soyez, 2012) or measured both injunctive and descriptive norms (e.g., Arvola et al., 2008; Urban, 2012). In most cases when they measured both, only one factor was retained in the factor analysis (e.g., Carrico et al., 2013). When both injunctive and descriptive norms were reported (e.g., White et al., 2009), we included only injunctive norms for further analysis. Only two articles measured solely descriptive norms (Fan, Wang, & Shen, 2019; Sopha & Klöckner, 2011). Four articles contained measurements that did not resemble subjective norms (Al-Mamun, Mohamad, Yaacob, & Mohiuddin, 2018; Davis et al., 2009; Ha & Janda, 2012), and are therefore not coded as subjective norms. While some authors refer to personal norms (e.g., Abrahamse & Steg, 2009), others mention moral norms (e.g., Hübner & Kaiser, 2006), or personal moral obligation (e.g., Chen & Tung, 2014). We coded variables as personal norms when the questions related to (moral) obligation, personal conviction, or feelings of guilt (most articles used a combination). In total, 157 articles included personal norms, subjective norms or both.

Individualism-Collectivism: We apply two widely used cultural frameworks – Hofstede and GLOBE – to detect cultural differences across societies in terms of collectivist values. Note that collectivist values are usually defined as opposite to individualist values (as the other end point of the same dimension). In Hofstede’s framework, collectivism (at the lower end of the dimension), represents a preference for a society in which “individuals can expect their relatives or members of a particular in-group to look after them in exchange for unquestioning loyalty” (Hofstede, 2001, p. 225). GLOBE distinguishes two dimensions: (a) institutional collectivism defined as the degree to which collective distribution of resources and collective action is encouraged, and (b) in-group collectivism defined as the extent to which individuals express pride, loyalty, and cohesiveness in their organizations or families (House et al., 2004). For each dimension, GLOBE distinguishes between values

Fig. 3. Funnel plots with Egger’s test for publication bias.
should be”) and practices (“as is”). GLOBE aims to detect both what people value and how they apply these values in practice (Maseland & Van Hoorn, 2009). Overall, the higher a country scores on a GLOBE’s dimensions, the more collectivist its culture is, while the higher the country scores on Hofstede’s dimension, the more individualist its culture is. Results are reported in Table 2. In case of missing values, we have imputed the average value of neighboring countries or clusters (see footnote of Table 2).

The Hofstede survey focused more on what people found relevant in their work situation (i.e., action-driven), while the GLOBE survey treated the differences between practices and values more abstractly (i.e., theory-driven; Hofstede, 2006; Brewer & Venaik, 2011; Maseland & Van Hoorn, 2009). Hofstede asked whether more time for personal and family life, good working conditions, security of employment, and adventure in the job were considered important. The GLOBE questionnaires contain statements like “In this society, aging parents generally live at home with their children” (in-group collectivist practices) or “In this society, being accepted by the other members of a group is very important” (institutional collectivist practices). For values, similar statements addressed whether people think this should be the case. Surprisingly, the overlap between Hofstede’s and GLOBE’s dimensions is very low (see Table 3). Hofstede’s individualism is most strongly

Table 2
Moderator Hofstede and GLOBE values for studied countries.

<table>
<thead>
<tr>
<th>Country (N studies)</th>
<th>N</th>
<th>Individualism-collectivism</th>
<th>Institutional Collectivism</th>
<th>In-group Collectivism</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Values</td>
<td>Practices</td>
<td>Values</td>
</tr>
<tr>
<td>Australia (13)</td>
<td>6061</td>
<td>90</td>
<td>4.40</td>
<td>5.75</td>
</tr>
<tr>
<td>Bahrain</td>
<td>241</td>
<td>25</td>
<td>5.27</td>
<td>5.63</td>
</tr>
<tr>
<td>Bangladesh</td>
<td>319</td>
<td>25</td>
<td>4.93</td>
<td>5.60</td>
</tr>
<tr>
<td>Belgium (3)</td>
<td>2731</td>
<td>75</td>
<td>4.69</td>
<td>5.18</td>
</tr>
<tr>
<td>Bosnia and Herzegovina</td>
<td>173</td>
<td>22</td>
<td>4.41</td>
<td>5.46</td>
</tr>
<tr>
<td>Brazil (2)</td>
<td>754</td>
<td>38</td>
<td>5.62</td>
<td>5.15</td>
</tr>
<tr>
<td>Canada (4)</td>
<td>1865</td>
<td>80</td>
<td>4.17</td>
<td>5.97</td>
</tr>
<tr>
<td>China (45)</td>
<td>24969</td>
<td>20</td>
<td>4.56</td>
<td>5.09</td>
</tr>
<tr>
<td>Cyprus</td>
<td>500</td>
<td>35</td>
<td>5.40</td>
<td>5.46</td>
</tr>
<tr>
<td>Czech Republic</td>
<td>252</td>
<td>58</td>
<td>3.85</td>
<td>4.06</td>
</tr>
<tr>
<td>Denmark (7)</td>
<td>4695</td>
<td>74</td>
<td>4.19</td>
<td>5.50</td>
</tr>
<tr>
<td>Egypt (2)</td>
<td>1390</td>
<td>25</td>
<td>4.85</td>
<td>5.56</td>
</tr>
<tr>
<td>Fiji Islands</td>
<td>205</td>
<td>14</td>
<td>4.49</td>
<td>6.20</td>
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<tr>
<td>Finland (3)</td>
<td>872</td>
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<td>4.11</td>
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<td>5.40</td>
<td>5.46</td>
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<td>Hong Kong (2)</td>
<td>529</td>
<td>25</td>
<td>4.43</td>
<td>5.11</td>
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<td>India (11)</td>
<td>3162</td>
<td>48</td>
<td>4.71</td>
<td>5.32</td>
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<td>Iran (7)</td>
<td>4075</td>
<td>41</td>
<td>5.54</td>
<td>5.86</td>
</tr>
<tr>
<td>Ireland</td>
<td>254</td>
<td>70</td>
<td>4.59</td>
<td>5.74</td>
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<tr>
<td>Israel (3)</td>
<td>4321</td>
<td>54</td>
<td>4.27</td>
<td>5.75</td>
</tr>
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<td>Italy (9)</td>
<td>3311</td>
<td>76</td>
<td>5.13</td>
<td>5.72</td>
</tr>
<tr>
<td>Japan (4)</td>
<td>1266</td>
<td>46</td>
<td>3.99</td>
<td>5.26</td>
</tr>
<tr>
<td>Lebanon (2)</td>
<td>735</td>
<td>40</td>
<td>4.76</td>
<td>5.76</td>
</tr>
<tr>
<td>Lithuania (3)</td>
<td>1213</td>
<td>60</td>
<td>4.06</td>
<td>5.76</td>
</tr>
<tr>
<td>Luxembourg</td>
<td>602</td>
<td>60</td>
<td>4.69</td>
<td>5.18</td>
</tr>
<tr>
<td>Malaysia (9)</td>
<td>2762</td>
<td>26</td>
<td>4.87</td>
<td>5.85</td>
</tr>
<tr>
<td>Mexico (2)</td>
<td>419</td>
<td>30</td>
<td>4.92</td>
<td>5.95</td>
</tr>
<tr>
<td>Netherlands (5)</td>
<td>1831</td>
<td>80</td>
<td>4.55</td>
<td>5.17</td>
</tr>
<tr>
<td>New Zealand (2)</td>
<td>1499</td>
<td>79</td>
<td>4.20</td>
<td>6.21</td>
</tr>
<tr>
<td>Nigeria</td>
<td>1360</td>
<td>30</td>
<td>5.63</td>
<td>5.48</td>
</tr>
<tr>
<td>Norway (2)</td>
<td>2020</td>
<td>69</td>
<td>3.94</td>
<td>6.04</td>
</tr>
<tr>
<td>Pakistan (6)</td>
<td>1765</td>
<td>14</td>
<td>4.76</td>
<td>5.45</td>
</tr>
<tr>
<td>Portugal</td>
<td>42</td>
<td>27</td>
<td>5.30</td>
<td>5.94</td>
</tr>
<tr>
<td>Russia</td>
<td>204</td>
<td>39</td>
<td>5.20</td>
<td>5.79</td>
</tr>
<tr>
<td>Saudi Arabia</td>
<td>611</td>
<td>25</td>
<td>5.27</td>
<td>5.63</td>
</tr>
<tr>
<td>Singapore</td>
<td>800</td>
<td>20</td>
<td>4.55</td>
<td>5.50</td>
</tr>
<tr>
<td>South Africa ¹</td>
<td>2004</td>
<td>65</td>
<td>4.34</td>
<td>5.45</td>
</tr>
<tr>
<td>South Korea (5)</td>
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<td>18</td>
<td>3.90</td>
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<tr>
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<td>406</td>
<td>51</td>
<td>5.20</td>
<td>5.79</td>
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<tr>
<td>Sri Lanka</td>
<td>440</td>
<td>35</td>
<td>4.71</td>
<td>5.32</td>
</tr>
<tr>
<td>Sweden (6)</td>
<td>5125</td>
<td>71</td>
<td>3.94</td>
<td>6.04</td>
</tr>
<tr>
<td>Switzerland (6)⁷</td>
<td>4598</td>
<td>68</td>
<td>4.66</td>
<td>4.97</td>
</tr>
<tr>
<td>Taiwan (10)</td>
<td>5875</td>
<td>17</td>
<td>5.15</td>
<td>5.45</td>
</tr>
<tr>
<td>Turkey (7)</td>
<td>4568</td>
<td>37</td>
<td>5.26</td>
<td>5.77</td>
</tr>
<tr>
<td>Uganda</td>
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<td>27</td>
<td>4.80</td>
<td>5.81</td>
</tr>
<tr>
<td>UK (13)</td>
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<td>89</td>
<td>4.31</td>
<td>5.55</td>
</tr>
<tr>
<td>USA (24)</td>
<td>13202</td>
<td>91</td>
<td>4.17</td>
<td>5.77</td>
</tr>
<tr>
<td>Vietnam (2)</td>
<td>950</td>
<td>20</td>
<td>5.01</td>
<td>5.80</td>
</tr>
</tbody>
</table>

Note. For Hofstede, we imputed the score of Uganda (East Africa), of Bahrain (Qatar), of Cyprus (Greece). For GLOBE, we imputed the score for Norway (Sweden), Luxembourg and Belgium (Netherlands, West Germany), Lithuania (Poland and Russia), Bulgaria (Turkey, Slovenia, Greece), Bosnia and Herzegovina (Slovenia, Albania), Cyprus (Greece), Lebanon (Israel, Turkey), Bahrain and Saudi Arabia (Qatar, Kuwait, Iran), Pakistan (India, Kuwait, Qatar, Kazakhstan), Fiji Islands (New Zealand, Philippines), Uganda (Zambia, Zimbabwe), Vietnam (Thailand, Philippines, Taiwan), Chile (Argentina, Bolivia), Sri Lanka (India), and Bangladesh (Thailand, Pakistan).

¹ For these studies we have averaged the scores available: the study in South Africa included Black and White participants, 1 study from Germany only included participants from East Germany, 3 included participants from East and West Germany, and one study in Switzerland included French as well as German speaking participants. The remaining German and Swiss studies only included West Germany, respectively German speaking population.
correlated with the model-implied correlation coefficients. Note that the off-diagonal elements of the implied correlation matrix are based on the SEM parameters and the diagonal elements of matrix $T^2$ show the between-studies heterogeneity in these model-implied correlation coefficients. Note that the off-diagonal elements of $T^2$ are fixed to zero. The SEM parameters are allowed to vary across studies as a function of the moderator variable. By regressing the SEM parameters on the moderators, one-stage MASEM allows an evaluation of how much of the model-implied correlations can be explained by the moderators. More precisely, the intercept describes the parameter value when the moderator is exactly zero, and the regression coefficient shows the impact of a one-point increase in the moderator on the parameter (Jak, Li, Kolbe, & Cheung, 2020). Note that parameters are part of different model-implied correlations (i.e., PBC relates to behavior directly but also indirectly via intention) which complicates quantifying the amount of explained variance by the moderators.

Given the relative strengths and weaknesses of these developments that allow for the inclusion of continuous moderators in structural path modeling (MASEM) (Bergh et al., 2014). Standard meta-analysis methods evaluate each bivariate relationship separately, and include the resulting correlation matrix as input for SEM, but MASEM evaluates the complete theoretical model (Sheng et al., 2016). Essentially, MASEM includes a variance-covariance matrix in estimating the synthesized effect sizes, while the standard methods ignore the correlations among the effect sizes. Traditionally, in the first stage, a pooled correlation matrix is estimated, which is then used in the second stage to estimate the proposed models using Weighted Least Squares estimation to SEM. In other words, heterogeneity is accounted for at stage 1, when a random effects approach is used. In stage 2, cultural differences can be explored with manually created subgroups, and using multi-group SEM in combination with restricting parameters to be equal across groups (Jak & Cheung, 2018). Although the random effects approach in stage 1 acknowledges heterogeneity, stage 2 treats heterogeneity as statistical noise, essentially being a fixed effects test (Cheung, 2015a). A recent development within MASEM allows testing continuous moderator variables to explain between-study variance (Jak & Cheung, 2019). To this end, the authors developed a one-stage MASEM approach that tests how small increases in the (standardized) moderators relate to the differences in model parameters.

In the following we discuss recent developments to explain heterogeneity, and how one-stage MASEM relates to them. First, to quantify heterogeneity at stage 2, Yu, Downes, Carter, and O’Boyle (2016) introduced a parametric bootstrap based on the effect size and its heterogeneity in order to generate many heterogeneous (positive definite) matrices to which a SEM model is fitted. From a distribution of effect sizes that is determined by the mean and standard deviation, Yu et al. (2016) randomly sampled values to create a heterogeneous population of effect sizes in stage 1. The resulting heterogeneity is pooled in an input matrix for stage 2 in addition to the pooled correlation matrix. Lastly, estimating each bootstrapped matrix results in a distribution for both coefficients and fit measures. This allowed Yu et al. (2016) to construct confidence intervals that reflect the heterogeneity accurately as is shown in their simulation studies. Cheung (2018) cautioned intervals may be valid for path coefficients but not for fit measures. Secondly, to account for the dependency among regression coefficients, Becker and Wu (2007) used regression coefficients as effect sizes in a multivariate regression analysis. By stacking all coefficients and the (pooled) covariance matrices, and identifying coefficients in each study with a design matrix, Becker and Wu (2007) estimated a generalized least squares regression weighted by the design matrix. This enabled them to calculate a variance-covariance matrix of the coefficients to indicate heterogeneity. Both developments enabled Cheung and Cheung (2016) to develop a parameter-based MASEM which explores how path coefficients, instead of bivariate correlations, vary across studies. This approach can be used to include continuous moderators. Instead of the bivariate correlation coefficients, they pooled estimated parameters from stage 1 (based on GLS) and included them in stage 2 to indicate heterogeneity in meta-analysis (Cheung & Cheung, 2016). This approach allowed each study to have different path coefficients even though the overall model holds across all studies. Most recently, Ke, Zhang, and Tong (2019) developed a parameter-based MASEM model in the Bayesian framework to overcome the limitations related to missing data and to allow the evaluation of model fit using Bayesian fit measures.

In contrast to these developments, one-stage MASEM models the heterogeneity as a function of the model-implied correlation coefficients, which are a function of the SEM parameters (Jak & Cheung, 2019). Specifically, the off-diagonal elements of the implied correlation matrix are based on the SEM parameters and the diagonal elements of matrix $T^2$ show the between-studies heterogeneity in these model-implied correlation coefficients. Note that the off-diagonal elements of $T^2$ are fixed to zero. The SEM parameters are allowed to vary across studies as a function of the moderator variable. By regressing the SEM parameters on the moderators, one-stage MASEM allows an evaluation of how much of the model-implied correlations can be explained by the moderators. More precisely, the intercept describes the parameter value when the moderator is exactly zero, and the regression coefficient shows the impact of a one-point increase in the moderator on the parameter (Jak, Li, Kolbe, & Cheung, 2020). Note that parameters are part of different model-implied correlations (i.e., PBC relates to behavior directly but also indirectly via intention) which complicates quantifying the amount of explained variance by the moderators.

Given the relative strengths and weaknesses of these developments that allow for the inclusion of continuous moderators in a structural path model analyzed at a meta-analytical level, we applied the one-stage MASEM approach developed by Jak and Cheung (2019). Note that this method makes use of full-information maximum likelihood estimation (FIML) which accounts for missing effect sizes using all the information present in the data. For an overview of random effects MASEM methods and a more elaborate discussion of FIML as used in one-stage MASEM, see Jak and Cheung (2019).

### 4. Results

First, we have analyzed the bivariate relationships using the fixed effects model. The fixed effects model assumes that each study belongs to the same population of studies and therefore only allows for conditional inference, i.e., the conclusions are restricted to the studies included in the analysis (Hedges & Vevea, 1998). We find that, for all relationships, the homogeneity test statistic Cochran’s Q significantly differs from zero (we only report the relationship between PBC and behavior, which obtained the lowest value: $Q_{PBC-B} = 939.88$, d.f. = 75). As the power of the Q statistic is low in a few studies, and conversely high in many studies, we also looked at the $I^2$ (Higgins, Thompson, Deeks, & Altman, 2003). All relationships have an $I^2 > 92\%$ which indicates strong heterogeneity. The random effects approach relaxes the assumption that all studies belong to the same population. When we estimate a mixed effects model including all individualism-collectivism dimensions as moderators, we find that the Hofstede dimension only

| Table 3 Correlation matrix of Hofstede and GLOBE values. |
|---|---|---|---|---|
| 1. Individualism-collectivism | 1 | -0.387 | 0.018 | -0.055 | -0.775 |
| 2. Institutional Collectivism (Values) | -0.507 | 1 | 0.075 | -0.605 | 0.532 |
| 3. Institutional Collectivism (Practices) | -0.218 | 0.306 | 1 | 0.295 | 0.205 |
| 4. In-group Collectivism (Values) | 0.064 | -0.603 | -0.013 | 1 | -0.092 |
| 5. In-group Collectivism (Practices) | -0.724 | 0.535 | 0.295 | -0.148 | 1 |

Note. The correlation among the countries included in the study ($N = 68$) is reported in the upper diagonal matrix; the correlation among all countries ($N = 116$) are reported in the lower diagonal matrix. Note that 13 countries in our sample are not included in a Hofstede index, and 37 countries are not included in GLOBE. See footnote Table 2 how we dealt with these missing values.
affect co-variances between PBC and subjective norms while in-group practices additionally affects the covariance between attitude and personal norms. The sensitivity analysis of these mixed effects models, in which we estimated the same models on the whole dataset excluding one study each analysis, showed that no single study changed this result. Additionally, from a methodological perspective, we explored whether the varying representativeness of the samples might have contributed to this heterogeneity. Using a random effects model at the bivariate level, we observe that there are no systematic effects of using a random versus a non-random sample. Those who participated in a Paper-and-Pencil-Interviewing (PAPI) study are also more likely to report a stronger intention-behavior link than participants in a Computer-Assisted-Web-Interviewing (CAWI) study. How these results might relate to representativeness remains unclear: it might be that the PAPI studies are more likely to select participants that are interested in the topic more than the CAWI studies that require less effort. Some PAPI studies used a convenience sample while others used a random sample from the national registry. Given the high variability among these approaches, it is unlikely that the systematic effect is due to representativeness. Another variable we analyzed was the type of sample. It seemed that youth (students, pupils) were more likely to report a strong intention-behavior link than residents. The latter was randomly sampled less often than the former. However, it might also be that young people are truly more likely to conduct certain behaviors than older people. Representativeness has many aspects, of which we only addressed a few here (i.e., sampling method, data collection method and sample characteristics).

The met SEM package pools the effect sizes per correlation using a random effects model (Cheung, 2015b), resulting in a synthesized correlation matrix (see Table 1). The pooled effect sizes range between 0.328 (relationship between behavior and subjective norms) and 0.531 (relationship between intention and attitudes; see lower triangle of Table 1). In a two-stage approach, these bivariate correlation coefficients are used as input for the second stage, estimating the fit of the models as depicted in Fig. 1. Instead, we use a one-stage approach that allows us to simultaneously estimate the synthesized correlation matrix and fit the model (with the statistical advantages as explained above). The fit of SEM models can be assessed using various test statistics, including chi-square, RMSEA, CFI, TLI, and BIC (3). Additionally, we analyze the explained variance of all endogenous variables to enable comparing model fit across models estimated on different samples.

According to the BIC value, Model 2 fits better compared to Models 3 and 4 (see Table 4). Model 3 and Model 4 show a good fit with respect to RMSEA and CFI but do not score well on TLI (below 0.95) and SRMR. The SRMR is interpreted as an indicator of good fit when it produces a value lower than 0.05 (Kline, 2011), while others argue 0.08 should be the cut-off value (Hu & Bentler, 1999). The SRMR indicates that there is still some remaining unexplained variance which might reflect the cultural differences that were not taken into account so far. Model 2 has the lowest SRMR value demonstrating that this is the best fitting model. Note that Model 1 has a much lower BIC value due to different sample size (and cannot be compared to the other models using this statistic).

With respect to explained variance of behavior, we find that all models explain between 33% (Models 3 and 4) and 32% (Models 1 and 2). For intention, we find that Model 1 has the lowest explained variance (40%), Models 2 and 3 have an intermediate level (44%, respectively 42%), and Model 4 has the highest explained variance (51%). As Model 1 has a lower explained variance with respect to intention and Model 2 has best model fit according to SRMR, RMSEA, TLI, CFI, and BIC we partially accept H1. Interestingly, the regular fit statistics show the superiority of Model 2 over Models 3 and 4.

The next step is to explore how the moderator values impact the model fit. We only allow the moderator values to affect the direct relationships between personal norms and other TPB variables. Hence, we exclude Model 1, test two effects for Models 2 and 3, and test one effect for Model 4. Table 5 shows that the Hofstede individualism-collectivism dimension explains variance between studies in Model 3 based on a $\chi^2$ test that compares the model with and without this moderator. The fit of Model 3 only improves when accounting for cultural variation in in-group collectivist practices. Overall, we find moderate support for H2, as only Model 3 shows a significant moderation effect (see Table 5).

Next, we are interested whether the individualism-collectivism dimensions of Hofstede and GLOBE explain systematic variance between the studies in terms of how personal norms relate to the TPB variables (H3). We test H3 in the best-fitting model (Model 2, see Table 5). To this end, we allow the continuous moderators to affect the direct relationships between personal norms and the TPB variables. The first seven rows of Table 6 describe the main effects of the model, i.e., the part of the relationship that is similar across countries.

When exploring the moderating effect of individualist-collectivist values on the model parameters associated with personal norms (specifically in Model 2), we observe that the relationship between personal norms and intention significantly differs between collectivistic and individualistic countries (see Table 6). In countries scoring high on GLOBE in-group collectivist practices, i.e., in the more collectivistic countries, personal norms are also less important in explaining intention ($\beta = -0.028, z = -2.03$). This effect implies that personal norms play a weaker role in societies that score higher on collectivism measured by in-group practices. Note that countries scoring high on in-group practices include India, Iran, Vietnam and China. Remarkably, this result is

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(3) The chi-square value measures how the theoretically expected correlation matrix resembles the observed correlation matrix. A high chi-square value means that the model does not represent the data very well. The absolute measure of root mean square error of approximation (RMSEA) shows how well the data approximates the true model and favors parsimonious models (i.e., penalizing for model complexity). The RMSEA is sensitive to misspecified factor loadings and misspecified latent structures. The Standardized Root Mean Square Residual (SRMR) compares the average of standardized residuals between observed and the hypothetical covariance matrix. Both the incremental measures comparative fit index (CFI) and Tucker-Lewis index (TLI) show how well the model improves the model fit compared to the null model, in which all variables are unrelated (in contrast to absolute measures, like RMSEA, that assess only the estimated model). Thus, higher correlations among variables would lead to higher CFI and TLI values. The TLI penalizes model complexity more severely than the CFI. Unlike the RMSEA, these indices are less sensitive to sample size (Browne & Cudeck, 1993; Hu & Bentler, 1999). Unlike the aforementioned fit statistics, the Bayesian information criterion (BIC) allows for comparing non-nested models. The BIC finds the model with the highest posterior probability by maximizing the marginal probability of the data. Li, Huang, and Weng (2017) have shown that BIC outperforms the Akaike information criterion (AIC) that is developed in line with the Kullback-Leibler (KL) information. Note that the BIC is dependent on the number of variables and observations.

---

Table 4

<table>
<thead>
<tr>
<th>Model</th>
<th>$\beta$ (d.f.)</th>
<th>RMSEA</th>
<th>SRMR</th>
<th>TLI</th>
<th>CFI</th>
<th>BIC</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Classical TPB</td>
<td>12.3 (2)</td>
<td>0.007</td>
<td>0.020</td>
<td>0.979</td>
<td>0.996</td>
<td>-15655.63</td>
</tr>
<tr>
<td>2. Extended TPB</td>
<td>4.5 (2)</td>
<td>0.003</td>
<td>0.010</td>
<td>0.994</td>
<td>0.999</td>
<td>-20124.236</td>
</tr>
<tr>
<td>3. Mediated TPB</td>
<td>71.7 (4)</td>
<td>0.011</td>
<td>0.052</td>
<td>0.917</td>
<td>0.978</td>
<td>-20080.591</td>
</tr>
<tr>
<td>4. Normative influence TPB</td>
<td>86.9 (4)</td>
<td>0.013</td>
<td>0.046</td>
<td>0.899</td>
<td>0.973</td>
<td>-20065.342</td>
</tr>
</tbody>
</table>

Note: These random effects results are obtained with one-stage approach to MASEM which simultaneously synthesizes the effect sizes and estimates the structural path coefficients. The BIC of the Classical TPB model is incomparable to the BIC values of the other models as a different set of explanatory variables and sample size is used (due to disregarding Personal Norms).
Table 5
The likelihood ratio test of the difference between model with and without moderated relationships.

<table>
<thead>
<tr>
<th>Model</th>
<th>Hofstede Individualism-collectivism</th>
<th>GLOBE In-group collectivist practices</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\chi^2$</td>
<td>$p$</td>
</tr>
<tr>
<td>2. Extended TPB</td>
<td>1.9</td>
<td>0.386</td>
</tr>
<tr>
<td>3. Mediated TPB</td>
<td>9.0</td>
<td>0.011</td>
</tr>
<tr>
<td>4. Normative influence TPB</td>
<td>$-106.3^*$</td>
<td>1.000</td>
</tr>
</tbody>
</table>

Note. The likelihood ratio test compares the likelihood values of the model with and without moderators, $df$ increase is 2 (Models 2 and 3) or 1 (Model 4), and follows a chi-square distribution asymptotically. The estimated matrix is not positive definite.

Table 6
Moderator analysis of Model 2.

<table>
<thead>
<tr>
<th>Moderator analysis</th>
<th>Hofstede Individualism-collectivism</th>
<th>GLOBE In-group collectivist practices</th>
</tr>
</thead>
<tbody>
<tr>
<td>B-BI</td>
<td>$0.370$</td>
<td>$10.34^{***}$</td>
</tr>
<tr>
<td>B-ATT</td>
<td>$0.266$</td>
<td>$11.62^{***}$</td>
</tr>
<tr>
<td>B-PFC</td>
<td>$0.153$</td>
<td>$5.67^{***}$</td>
</tr>
<tr>
<td>B-PH</td>
<td>$0.191$</td>
<td>$9.05^{***}$</td>
</tr>
<tr>
<td>B-PN</td>
<td>$0.165$</td>
<td>$4.10^{***}$</td>
</tr>
<tr>
<td>B-PF</td>
<td>$0.228$</td>
<td>$6.97^{***}$</td>
</tr>
<tr>
<td>B-PH</td>
<td>$0.197$</td>
<td>$9.77^{***}$</td>
</tr>
<tr>
<td>B-PF</td>
<td>$0.015$</td>
<td>$1.13$</td>
</tr>
</tbody>
</table>

Note. *significant at the 0.05 level ($Z$ values > 1.96), ** significant at the 0.01 level ($Z$ values > 2.56), ***significant at the 0.001 level ($Z$ values > 3.29).

not found for Hofstede’s individualism. Although the sign of the effect goes in the same direction (i.e., positive, as more individualistic countries are more likely to have a strong effect of personal norms on intention), it fails to reach significance. Surprisingly, the personal norms do not affect behavior differently across studies. Also, Hofstede’s individualism does not explain any cross-cultural variance in the relationship between personal norms and intention or behavior. In sum, we find partial support for H3: In countries scoring high on in-group practices, personal norms seem to play a weaker role in explaining intention, but this effect fails to reach significance for Hofstede’s individualism-collectivism.

5. Discussion

Using a novel approach that integrates meta-analytical techniques with SEM, and simultaneously allows for continuous moderators, we explore how personal norms likely affect the TPB model relationships across cultures. Our findings offer useful implications for scholars and practitioners for the use of TPB across cultures as well as for pro-environmental research. Although many theoretical representations of the TPB model that includes personal norms are plausible, our analysis that compares 3 leading alternative models, suggests that the model in which personal norms directly and indirectly affects behavior via behavioral intention (Model 2 – Extended TPB) shows the best model fit. Whereas Model 1 (Classical TPB) also shows good fit, Models 3 and 4 (Mediated TPB; Normative Influence TPB) demonstrate relatively poor fit. A key implication involves the need to re-consider how to integrate personal norms in the TPB model when conducting cross-culture comparisons. At least in a context like environmental behavior – a context that involves moral aspects (Kaiser, 2006), adding personal norms – that are often equated with moral norms (Nordlund & Garvill, 2005; Stern, 2000) – to the TPB model moderately improve the model fit.

Based on two cultural dimensions from the Hofstede and GLOBE frameworks, we analyzed whether parameters of this model differ across cultures. Our results suggest that GLOBE can explain country differences in the performance of the TPB model better than Hofstede when considering two individualism-collectivism dimensions of these frameworks. Collectivism measured by these frameworks does explain some of the cross-country variance in the parameters of personal norms in Models 2, 3 and 4. Specifically, we find that, in Model 2, personal norms affect intention to a lesser extent for countries scoring high on GLOBE in-group collectivist practices. This leads us to conclude that personal norms are less likely to influence intention (directly) in collectivistic countries. The effect is significant though moderate, and our sensitivity analyses show that the moderation effect holds on every combination of studies (i.e., the sample from which we exclude one study each analysis), where 212 out of 254 subsamples show a significant moderation effect at a 95% confidence interval.

On a side note, the GLOBE in-group collectivist values confirm our findings: The more collectivist the country, the weaker personal norms relate to intention ($\beta = -0.053$, $z = -3.86$). The low convergent validity with the other dimensions indicates that in-group collectivist values reflect other aspects of collectivism than those being measured by Hofstede’s individualism and GLOBE’s in-group practices. Even though in-group values do not relate strongly to the other individualism-collectivism dimensions (see Table 3), these results show that personal norms may differently affect intention depending on cultural collectivist values of the country in which the study is conducted. Among countries appreciating in-group values are Canada, Sweden, Norway and New Zealand; countries that are traditionally considered to be individualistic. The reason might be that people living in individualistic societies are more likely to appreciate values that are not so common in these countries (marginal utility theory, see Maseland & Van Hoorn, 2009).

All in all, we tentatively conclude that personal norms may play a smaller role in collectivistic countries in determining intention than in individualistic countries according to Model 2. Remarkably, our analyses show that Hofstede’s theoretical framework is unable to explain the between-study heterogeneity for the other models. With respect to subjective norms, Hassan, Shiu, and Parry (2016) find that Hofstede’s individualism could not explain cross-cultural variation in its relationship with intention. Brewer and Venaik (2011) also show that the Hofstede’s framework does not relate to macro-economic indicators in the same way as GLOBE dimensions, which could indicate that the dimensions reflect different aspects of collectivism. However, the correlation between Hofstede and (some) GLOBE dimensions illustrate convergent validity. While Hofstede’s framework was developed to measure work attitudes cross-culturally (based on a work attitude survey among IBM employees), GLOBE aims to detect both what people value and how they apply these values in practice (Brewer & Venaik, 2011). This more practical approach could lead to collectivism scores that are closer to what people actually experience in everyday life, and therefore more likely to be related to environmentally friendly choices. On the other hand, Hofstede argues that people struggle to answer abstract questions about unfamiliar issues they are less likely to take the actual situation as the norm (Hofstede, 2006, p. 886). This might explain the negative relationship between GLOBE practices and values. Mase- land and Van Hoorn (2009) argue that the negative relationship might reflect diminishing marginal utility, a concept from microeconomics; people are likely to value those values of which they can have little of. Hence, when asked about certain values, they are likely to affirmatively respond to the “as is” questions while not to the “should be” questions due to the decreasing relative importance of common (and vice versa for rare values).

With respect to the relationship between intention and behavior, we find no moderator effect of collectivism. Similarly, Hassan et al. (2016) find no cross-cultural variation in the relationship intention and behavior among 67 studies. In contrast, Kaiser et al. (2008) find that the
relationship between intention and behavior differs between the four countries studied when integrating anticipated guilt into the TPB model. Based on a subset of our data, and using a mixed regression model, Morren and Grinstein (2016) find that individualistic countries (based on median split) demonstrate a stronger relationship between intention and behavior. This is no longer supported by the additional data and analyses reported in this paper. Park, 2000 argues that attitudes are a multidimensional construct, with social attitudes reflecting the person’s belief about social aspects of behavioral outcomes and personal attitudes reflecting behavioral outcomes that affect the self. Park separately measures these components and shows that social attitudes could influence intention more strongly in collectivistic countries and personal attitudes influence intention more strongly in individualistic countries (Park & Ha, 2012).

The findings confirm our initial hypothesis that personal norms play a role in how TPB variables affect behavior, and that this role moderately differs across cultures. This would suggest that the inclusion of subjective norms as part of the TPB model is not sufficient to account for cross-cultural variation. Instead, there is a need for a multidimensional construct of norms to take into account the more intricate relationships between norms and the TPB variables. Further, although we find the distinction between subjective and personal norms to be meaningful, most existing work has studied one type of subjective norms: Descriptive norms. Similarly, Klöckner (2013) finds that personal norms improve the explanation of intention and mediate the influence of social norms on intention. While our work adds to the understanding of how these relationships differ cross-culturally, future work should also account for how personal norms interact with injunctive norms across cultures.

Finally, it is noteworthy to discuss how our findings relate to a general criticism of TPB and more broadly theoretical development based on survey research. Kaiser, Merten, and Wetzel (2018) argue that all TPB variables are indicators of an "environmental attitude." Therefore, self-reported attitudes, norms and behaviors are considered manifestations of a unidimensional factor (Kaiser & Wilson, 2019; Kaiser, Byrka, & Hartig, 2010). According to this theory, verbally claiming (environmental) behavior is easier than performing this behavior due to costs or other difficulties. Furthermore, in observing the behavior one cannot distinguish between motivations for the behavior (e.g., eating organic food looks the same even if motivated by health reasons, the environment, or taste). The same problem concerns behaviors that are verbally reported. The formal model underlying this theory is the Rasch model, in which behaviors and attitudes are ranked in terms of difficulty both in the terms of the measurement and the person’s ability (Fischer, 1987). This model challenges not only the theorized relationships among the TPB variables but also the approach taken by Ajzen and Fishbein (1980). The one-factor model as proposed by Kaiser et al. (2018) was tested and slightly outperforms the alternative TPB models (BIC = −20188, RMSEA = 0.003, SRMR = 0.023, TLI = 0.99, CFI = 0.99). Further research could investigate why the TPB variables might reflect just one dimension, and critically examine the TPB theory.

As a last remark, we acknowledge that common method bias might artificially increase the correlations among the TPB variables (including personal norms). To correct for this bias, we would need to separate the measurement model from the structural model, which is impossible with pooled correlations. Even more, common method bias might differ across cultures; between countries (e.g., Van de Vijver & Leung, 2000; Van Herk, Poorington, & Verhallen, 2004), but also within countries (e.g., Morren, Gelissen, & Vermunt, 2011), which further complicates the disentanglement of bias and content.

CRediT authorship contribution statement

Meike Morren: Data curation, Formal analysis, Writing – original draft, collected the data, coded the data, analyzed the data, was responsible for managing the research project and wrote the manuscript. Amir Grinstein: Data curation, Conceptualization, Writing – original draft, collected the data, coded the data, engaged in the conceptualization part and wrote the manuscript.

References


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