Predicting the Revisit Intention of Volunteer Tourists Using a Merged Model Consisting of Theory of Planned Behavior and the Norm Activation Model

ABSTRACT

Despite the importance of the theory of planned behavior (TPB) and norm activation model (NAM) in explicating revisit intention, predictions based on the merging of these theories remain sparse in the youth volunteer tourism segment. To understand revisit intention formation, a meta-analysis is performed to draw a macro conclusion using prosocial studies as a representative of volunteer tourism in investigating the predictive power of the aforementioned merged theories. Subsequently, latent growth curve modeling is applied to extend the understanding of tourist type identification to volunteer tourism research. The introduction of NAM into TPB marginally adds value to predictive power.

Keywords: volunteer tourism; theory of planned behavior (TPB); norm activation model (NAM); meta-analysis structural equation modeling (MASEM); Bayes factor (BF); latent growth curve modeling (LGCM); temporal effects

Introduction

Volunteer tourism is a form of sustainable tourism (Raymond & Hall, 2008) that allows collaboration between tourists and stakeholders in various ways to fulfill the needs of a local community, such as environmental restoration, medical support, or educational assistance (McGehee & Andereck, 2008). In contrast with mass tourism, a unique feature of volunteer tourism is that it simultaneously provides the personal fulfillment of participants and the development of local communities (Han, Meng, Chua, Ryu, & Kim, 2019). Scholars have found that volunteer tourists can improve their self-development through volunteer tourism (Han, Meng, et al., 2019; Pan, 2017); such improvement is the primary motivation for participating in this type of tourism (Han, Meng, et al., 2019). Given these characteristics, volunteer tourism has drawn youth travelers worldwide who aim to enhance their personal development (Sin, 2009). In addition, the market value of volunteer tourism consecutively exhibited a noticeable growth rate of up to 63% in 2018 from 40% in 2017 and 9% in 2016 (Voluntary National Review, 2019). Approximately 1.6 million travelers are estimated to participate in volunteer activities per year (Bargeman, Richards, & Govers, 2018). Furthermore, the volunteer tourism market of youth travelers is regarded as one of the fastest-growing tourism markets, with a value of approximately USD 190 billion (Meng, Ryu, Chua, & Han, 2020). Destination marketing organizations in various countries have attempted to promote volunteer activities to develop the experience of youth tourists. For example, South Korea, which is one of the most active countries in terms of volunteer tourism, has initiated various programs for young travelers who intend to improve their experiences and skills (Lee & Lina Kim, 2018; Steele, Dredge, & Scherrer, 2017). Given the significance and unique characteristics of volunteer tourism, prosocial scholars have recently highlighted the need to scrutinize behavioral intention among youth tourists (Meng et al., 2020), particularly the factors that determine their intention to return to an explored destination. Investigating behavioral intention among the youth segment of volunteer tourism is advantageous considering the scarcity of youth traveler studies. Destination marketing organizations can understand how the revisit intention of this tourist group is formed.

On the basis of the prior literature on revisit intention, researchers have agreed that two salient factors, namely, self-interest and prosocial motives, can clearly explain the formation of tourists' revisit intention (Shin et al., 2018). Consistent with attitudinal theories, the first motive supports the idea that the behavior to perform pro-environment actions is driven by a tourist's interest (Shin et al., 2018); this idea can be generally explained by theory of planned behavior (TPB). In contrast with the first motive, the prosocial motive is supported by the norm activation model (NAM) (Onwezen, Antonides, & Bartels 2013). NAM posits that an individual is willing to act, even though such an action creates a burden to him/her, when moral norm is activated (Onwezen, Antonides, & Bartels, 2013). Given this rationale, numerous attempts have been made to merge NAM with TPB to improve the explanatory power of the intention model in the general prosocial or pro-environmental context (Shin et al., 2018; Zhang et al., 2018). In the case of volunteer tourism, however, the examination of revisit intention formation (Meng et al., 2020), especially among youth tourists (Han, Meng, et al., 2019), has received minimal attention. In particular, only one volunteer tourism study has investigated revisit intention based on TPB. More specifically, Lee and Lina Kim (2018) conducted a meta-analysis to perceive the overall predictive power of TPB in behavioral intention and then paved the way to an underexplored but very important area of volunteer tourism. Although their study provided a broad insight into the volunteer tourism by conducting the meta-analysis, and the authors followed up with the examination in the volunteer tourism using the TPB, their study contains several methodological limitations, which can adversely affect the validity of their conclusion. First, the synthesis process in their meta-analysis was superficial; correlation coefficients were presented without an in-depth investigation of the reliability and validity issues (e.g., publication bias). Second, only 12 articles were included in the analysis, 11 of which were in the general tourism context and only one pertained to pro-social tourism. This condition could potentially and adversely affect the findings' validity. Lastly, the influence of each TPB component was not appropriately quantified. The beta coefficient, which is an indispensable part of meta-analytic nowadays, was missing. With the increasing demand to study the effect of "mediators" (i.e., Meng et al., 2020), scholars increasingly adopt structural equation modeling (SEM) as a tool to examine the mediating effect of variables within a model (i.e., Garay, Font, & Corrons, 2019; Vesci, 2019). We argue that traditional meta-analysis, which uses only descriptive or correlation coefficients, is inadequate for contemporary behavioral studies. Our study applies meta-analysis SEM (MASEM), which, unlike the traditional meta-analysis, provides a deeper understanding of the extent to which each variable interacts with others within the nomological network. To our knowledge, our study is among the first to address such demand by using MASEM in the pro-social/environmental tourism context. Besides, the most recent meta-analytic literature is based on published articles until 2014, whereas this study utilizes 22 relevant studies up to 2019. Our study fills the addressed research gaps and delivers the most up-to-date information (22 selected relevant articles).

Moreover, the previous volunteer tourism literature has rarely investigated revisit intention with multiple periods. This traditional practice implicitly assumes that revisit intention is fixed across time. However, revisit intention fluctuates over time (Jang & Feng, 2007); thus, we argue that understanding the movement pattern of tourists' revisit intention from a time perspective is imperative for scholars and practitioners. Therefore, relaxing the constant revisit intention assumption across time is worthy of research. Jordan, Bynum Boley, Knollenberg, and Kline (2018) relaxed revisit intention's constant assumption by partitioning revisit intention into three time frames and by using SEM to investigate this phenomenon. Given the limitation of traditional SEM, their analyses were not conducted simultaneously and did not account for variations in participants' revisit intention across time. Consequently, the questionable issue of the comparability of temporal effects across time arises. As a well-designed methodology, latent growth curve modeling (LGCM), which belongs to the same family as SEM, can provide stronger support than traditional SEM because it entails the simultaneous analyses of temporal effects (Manosuthi, Lee, & Han, 2020). LGCM is a combination of traditional SEM and repeated measure design. Thus, it can account for measurement errors and identify the trajectory pattern of each participant across time (Curran, Obeidat, & Losardo, 2010). To improve understanding of the temporal effect of the revisit intention of young travelers in volunteer tourism, we divided revisit intention into short-term, mid-term, and long-term, and then simultaneously analyzed these temporal effects by using LGCM.

Considering the aforementioned gap, we divide the current research into two studies. Using prosocial tourism as a representative of volunteer tourism, the first study aims to verify the predictive power of the merged NAM and TPB framework through the meta-analysis of 22 relevant studies. The second study aims to simultaneously investigate the predictive power of the merged NAM and TPB framework and examine the temporal effects of the revisit intention of young travelers in volunteer tourism by using LGCM. By focusing on volunteer tourism, which is a specific type of prosocial tourism, this research contributes to theoretical development in the revisit intention formation literature and provides valuable information to practitioners and destination marketing organizations regarding the temporal revisit intention of young tourists. Such information can assist practitioners in developing tourism products and services that favorably affect revisit intention.

Theoretical framework

Theory of Planned Behavior

Using a psychological theory to explain behavior, TPB posits that an action can be rationally justified by the intention to engage in a specific behavior, which is the most critical factor. Subsequently, this intention to perform can be illustrated through three predictors that can be divided into volitional and non-volitional elements. Under the scope of TPB proposed by Ajzen (1991), attitude is coined as an individual judgment based on an individual's favorability to perform a particular action. subjective norm is a behavior that relies on the approval or disapproval of other people. Perceived behavioral control refers to how individuals discern the ease or difficulty of completing such action. While attitude and subjective norm can be categorized as volitional elements, perceived behavioral control is regarded as a non-volitional component (Kim & Han, 2010). The empirical literature shows that attitude, subjective norm, and perceived behavioral control jointly improve the predictive power of behavioral intention in pro-environmental and pro-social behavior. Although TPB is widely considered a powerful weapon for examining an individual's behavior, several scholars have noted its weaknesses (Shin, Im, Jung, & Severt, 2018); TPB occasionally fails to achieve an acceptable accuracy rate when predicting behavioral intention. One possible reason for such inadequacy is that TPB misses diverse facets outside the scope of volitional and non-volitional aspects (Han & Kim, 2010; Han & Yoon, 2015).

Norm Activation Model

Proposed by Schwartz (1977), NAM is created from a pro-social perspective. Thereafter, NAM has become popular for elaborating behavioral intention in various fields (Han & Kim, 2010), such as public transportation usage (Bamberg, Hunecke, & Blöbaum, 2007), pro-environmental behavior meta-analysis (Bamberg & Möser, 2007), green hotel (Han, Hsu, & Sheu, 2010), empirical pro-environmental intention (Onwezen, Antonides, & Bartels, 2013), saving electricity by reusing towels (Cvelbar, Grün, & Dolnicar, 2017; Kiatkawsin & Han, 2017), environmentally responsible convention attendance (Shin, Im, Jung, & Severt, 2017), and eating local food that uses organic menus (Shin et al., 2017, 2018). NAM consists of three core components: awareness of consequence (AC), ascription of responsibility (AR), and personal norm (personal norm). AC refers to "whether someone is aware of the negative consequences for others or for other things one values when not acting pro-socially" (De Groot & Steg, 2009). AR refers to the "feeling of responsibility for the negative consequences of not acting pro-socially" (De Groot & Steg, 2009). personal norm is the "moral obligation to perform or refrain from a specific action" (Schwartz, 1977).

In accordance with the original model, personal norm is the most influential factor that engenders pro-social behavior (Shin et al., 2018). Although the NAM can be viewed as sequential or non-consecutive, the generally accepted mechanism for activating personal norm is sequential (Han, 2014). Consequently, this study focuses on personal norm because it is the core feature of NAM (Fornara, Pattitoni, Mura, & Strazzera, 2016). Although NAM has been perceived as one of the most appropriate frameworks for examining pro-social and pro-environmental behavior (Han, 2015; Zhang, Wang, & Zhou, 2013), this framework still misses volitional and non-volitional aspects (Fornara et al., 2016). Hence, the integration of TPB and NAM into a single framework is logical.

Development of hypotheses

In general, the results of meta-analytic studies point out that the intention of an individual to act is the most potent determinant of real behavior. For example, Armitage and Conner (2001) conducted a meta-analytic review of 185 studies that focused on the efficacy of TPB. The most effective predictor in the original TPB framework is attitude, which has an effect size of (r^+) 0.49, followed by the association between perceived behavioral control and behavioral intention, with r^+ = 0.43. Meanwhile, $r^+$of subjective norm is 0.34. Han and Stoel (2017) carefully selected 30 articles related to socially responsible consumer behavior and performed a meta-analytic review of TPB. Their findings exhibit that, in the general pro-social context, the effect sizes of attitude (r^+ = 0.53) and subjective norm (r^+ = 0.50) are similar to that of attitude. Gao, Mattila, and Lee (2016) confirmed the salience of attitude. Such analysis regards attitude as a subset of consumers' internalized perception, suggesting an actual moderate effect size of 0.3177. The aforementioned findings reinforce the positive relationship between attitude and behavioral intention.

To hypothesize from the preceding analysis that attitude exhibits a positive relationship with revisit intention may be thought-provoking. However, recent studies in the context of sustainable tourism and its related fields have failed to detect any relationship between attitude and revisit intention. For example, in the case of volunteer tourism, Lee and Lina Kim (2018) performed a meta-analytic analysis of 12 studies in the first stage before conducting subsequent research on volunteer tourism. They found moderate effect sizes of attitude (r^+ = 0.43), subjective norm (r^+ = 0.41), and perceived behavioral control (r^+ = 0.52) in the first stage. However, in Lee and Lina Kim (2018)'s subsequent analysis on volunteer tourism, attitude exhibits a statistically insignificant impact on behavioral intention, and the effect size from this analysis is extremely low (r = 0.008). Chavarria and Phakdee-auksorn (2017) studied international tourists' attitude regarding street food in Thailand and found an insignificant effect of cognitive attitude on repurchase intention, while subjective norm and perceived behavioral control exert significant weight on repurchase intention. Sun, Law, and Schuckert (2020) examined the validity of TPB in the context of mobile payment-based hotel reservations. Empirically, a relationship between attitude and repurchase intention was not detected. In the context of green environment, Nguyen, Nguyen, and Hoang (2019) found that attitude toward the environment cannot predict green consumption intention. Recently, Juschten, Jiricka-Pürrer, Unbehaun, and Hössinger (2019) gathered data from 877 participants to examine the predictive validity of TPB in the pro-environmental context. To predict behavioral intention, the findings found that the only insignificant predictor is attitude. It is important to note that recent empirical studies found that although attitude exhibited a significant effect of attitude on green consumption, its predictive power is weakest compared with subjective norm and perceived behavioral control (Carfora et al., 2019; Juschten et al., 2019). Hence, our study presumed that in the context of volunteer tourism, attitude can either be weak or even have no effect on revisit intention if collectively tested with other predictors as suggested by the abovementioned empirical examples. However, in the case of separately testing between attitude and revisit intention, previous literature has an agreement that attitude does affect revisit intention. Therefore, we proposed that when separately tested in the context of volunteer tourism,

H1: Attitude exhibits a positive relationship with revisit intention.

Subjective norm can be interchangeably called social norm in the environmental context (Han & Hyun, 2017). The previous literature supports the importance of other people's behaviors in shaping an individual's behavior (Han, Lee, Chua, & Kim, 2019; Kim, Lee, & Hur, 2012; Li & Wu, 2019; Teng, Wu, & Liu, 2015). Similarly, a behavior disapproved by a social group can have a negative impact on how a person behave in any situation, including pro-social and pro-environmental behaviors (Yamada & Fu, 2012). In the general tourism context, Olya and Han (2019) examined tourists' behavioral intention to participate in space tourism. The findings emphasized the significant effect of the predictive power of social motivation on tourists' intention to participate in space tourism. Although the results of subjective norm in general studies imply that subjective norm tends to have the weakest predictive power (Godin & Kok, 1996; Sheppard, Hartwick, & Warshaw, 1988), previous meta-analytic studies in the pro-social and pro-environmental context present the different result, i.e., that subjective norm is an indispensable factor in triggering tourists' behavioral intention (Han & Stoel, 2017; Klöckner, 2013; Lee & Lina Kim, 2018). Hence, we postulated that

H2: Subjective norm exhibits a positive relationship with revisit intention.

Perceived behavioral control is a salient component within the TPB framework because it is regarded as a non-volitional aspect that improves the explanatory power of TPB (Han & Hyun, 2017; Han, Meng, & Kim, 2017). Moreover, meta-analytic reviews have emphasized that perceived behavioral control is an accurate factor for forecasting tourist's intention to behave pro-socially (Klöckner, 2013). For example, one of the meta-analytic result found that the relationship between perceived behavioral control and behavioral intention in hotel and tourism services among Asian consumers is stronger than that in the general context (Han & Stoel, 2017). This result may be attributed to this relationship being connected with the availability of supplied products or services, particularly in the case of volunteer tourism, which is considered a micro niche market. Given that tourists have limited choices in joining this micro niche market; thus, the impact of perceived behavioral control can surpass those of the other factors within the TPB framework. Therefore, we hypothesized that

H3: Perceived behavioral control exhibits a positive relationship with revisit intention.

As the core of the NAM framework, personal norm is perceived to enhance the exploratory power to predict pro-social behavioral intention when used together with the TPB framework. Han and Hyun (2017) indicated that in examining pro-environmental behavior, prediction capability is significantly enhanced by 2% over TPB. The results from various meta-analytic studies support the claim that incorporating personal norm into the original TPB can improve the overall explained variance of behavioral intention (Bamberg & Möser, 2007; Han & Stoel, 2017; Klöckner, 2013). For example, Han and Stoel (2017) conducted meta-analysis of 11 independent pro-social studies to perceive the effect of introducing personal norm into the original TPB; they found that the overall explained variance increased from 39.7% to 41.3%. Kiatkawsin and Han (2017) also underscored the effect of personal norm on behavioral intention. Hence, personal norm can positively affect pro-social and pro-environmental behavior when it is already activated. Considering this empirical evidence, the current study presumes that

H4: Personal norm exhibits a positive relationship with revisit intention.

Researchers tend to modify the original TPB to improve the predictive power of analysis; therefore, subjective norm is one of the modifications assumed by scholars to have a positive impact on attitude (Ryu & Jang, 2006; Wu & Lin, 2007), and several researchers have extended it to relate to personal norm (e.g., Klöckner, 2013). The implication is that attitude and personal norm can also be regarded as mediators between subjective norm and behavioral intention. This idea is based on the fact that a person’s attitude and personal norm can be shaped to a certain extent by how society perceives an object as explained by social identity theory (Stets & Burke, 2000). In addition, social or subjective norm can be viewed as social glue that connects a person to society. This bond encapsulates a person’s value or attitude (Warner & Joynt, 2002). Hence, assuming that attitude and personal norm can be shaped by social or subjective norm is logical.

Empirically, social relationship is identified as one of the key predictors of cognitive attitude in the context of volunteer tourism (Bailey & Russell, 2010). In the case of green hotels, Teng et al. (2015) observed the positive impact of subjective norm on attitude, and simultaneously, attitude acts as a potential mediator between subjective norm and behavioral intention. Such conclusions can be prevalently found in previous studies (e.g., Han and Kim 2010, Ryu and Jang 2006, Tsai 2010, Wu and Lin 2007). Although the literature has pointed out the importance of connecting subjective norm with attitude, Garay et al. (2019) examined TPB and its extension to the context of sustainability-oriented innovation in tourism and found that social norm exhibits no relationship with attitude. In our study, we assumed that subjective norm exerts a significant influence on tourists' attitude. Hence, we hypothesized that

H5: subjective norm exhibits a positive relationship with attitude.

From the aforementioned argument, personal norm is social-bound rather than social-free. Being social-bound, tourists tend to value the destinations they visit differently based on the opinion of their peers. Hence, subjective norm can gradually form personal norm. In empirical research, meta-analytic studies have confirmed this idea. For example, Klöckner (2013) suggested that subjective norm is linked to personal norm, expanding the role of the latter to be a potential mediator between subjective norm and behavioral intention. Similarly, this relationship has been explored and confirmed in various settings, such as hotel–restaurant image (Han & Hyun, 2017), green lodging (Han 2015), and underwater scuba diver's behavior (Ong & Musa, 2011). On the basis of several pieces of evidence, we presumed that

H6: subjective norm exhibits a positive relationship with personal norm.

Methodology

Study 1: MASEM

To achieve the first objective, we conducted MASEM to draw conclusions about the effect size of related variables within the TPB/NAM framework in the context of sustainable tourism. That is, it was broadly divided into pro-social and pro-environmental behavioral intention. Hence, the unit of analysis for our first study was peer-reviewed articles related to TPB or NAM within the scope of sustainable tourism.

Sampling design

The search process was performed on October 1, 2019. Retrieving Social Sciences Citation Index studies from the Web of Science database and using an Internet search engine, we searched for relevant articles with the keywords "Theory of Planned Behavior" (n = 253) or "Norm Activation Model" (n = 22) plus related specific terms to fit the volunteer context (e.g., volunteer tourism, green tourism, pro-social tourism, pro-environment tourism, and volunteer tourism). A total of 151 articles were identified. Subsequently, all the identified articles were read carefully twice. To make our sample pertinent to the objective, we delimited our sample to contain information related to sustainable tourism or sustainable behavior. Given that meta-analysis requires the calculation of effect size, several articles that were previously identified as relevant to the point were excluded due to incomplete presentation or missing correlation matrix. Eventually, 22 usable articles were left. Table 1 summarizes the related studies and all available correlation pairs used in the meta-analysis.

[Insert Table 1]

Analysis design

In the meta-analysis, we aim to quantify the effect size of each pair between predictive variable and behavioral intention. Unlike the fixed-effects paradigm, the random-effects method allows the existence of between-study variances. Moreover, this method assumes that the differences in effect size of each study result from sampling error, implying that the random-effects approach enable researchers to generalize their findings. Therefore, we select random effects with restricted maximum likelihood (REML) as our method for quantifying effect size. To estimate the effect size of the study, let θ_i be the true effect size of study i, and μ denotes the average effect size. v_i is the known within-study error variance, and τ^2 is the unknown between-study error variance. Hence, the effect size can be calculated as follows:

$$\theta_i = \mu + v_i + \tau^2.$$

After obtaining the effect size θ_i, we calculate the heterogeneity statistics to examine the reliability of all the quantified effect sizes, which were obtained across all available studies. Given that each study has different underlying methods and sample characteristics, the problem of variability among the true effect size will be likely encountered (τ^2). We select τ^2 and i^2 statistics to examine this heterogeneity effect. To arrive at i^2, we start by calculating the weighted squared deviations of the effect size. Let Q be the weighted squared deviations of the effect sizes. Then, Q can be expressed as follows:

$$Q = \sum_i w_i \left(y_i - \hat{\theta}\right)^2.$$

Hedges and Olkin (2014) indicated that i^2 can be directly calculated as the variability percentage of effect sizes resulting from the true difference among sample studies; thus, the unexplained variance percentage in effect size can be demonstrated (Del Re, 2015).

$$i^2 = \left(\frac{Q - df}{Q}\right) x\ 100$$

If $i^2 = 0$, then the sampling error is only caused by the heterogeneity in the summary of effect sizes. If $i^2 = 100$, then the total variability that occurs in this analysis is attributed to the true heterogeneity from between-study errors. The interpretation is direct, namely, low (25%), medium (50%), and large (75%).

After we obtain a complete set of correlation matrix generated from the meta-analysis, we subsequently perform SEM on the basis of the correlation matrix. During this stage, hierarchical analysis is conducted to perceive the marginal effect of introducing NAM into the original TPB. Lastly, Monte Carlo simulation is implemented to estimate the power of SEM analysis for Study 2.

Study 2: Empirical study (volunteer tourism in South Korea)

To achieve the second objective, all the proposed hypotheses were tested separately and collectively via covariance-based SEM. For the third objective, revisit intention was investigated by extending to three timeframes. LGCM was implemented to capture the latent intercept and slope factors. To increase accuracy, we introduced the BF technique in addition to the conventional *p*-value.

Sampling and measurement designs

The initial version of the survey questionnaire was pretested by 10 academics in the hospitality and tourism department. A slight modification was made on the basis of their feedback. In addition, a pilot test was conducted among 89 young students (youth travelers) in the hospitality and tourism department. The questionnaire was then perfected by two professors whose major is tourism management. The original version of the questionnaire in English was translated into Korean using a back-to-back method.

Data collection was conducted during the Good News Corps Festival, a nonprofit religious festival, in spring 2019. Many religious volunteer tourists participated. Youth travelers who voluntarily completed a nonprofit global volunteer tourism program for 1 year were the major participants along with their family members. The questionnaire was distributed to volunteer tourists during break time. All the tourists voluntarily participated in the survey. They were requested to recall their volunteer tourism experiences and then answer the questions in the survey questionnaire. The completed questionnaire was returned on-site. After checking the completeness of the questionnaire, a USB that cost approximately US30.00 was given to the participants as a token of appreciation. We obtained a total of 376 usable responses through this process.

Analysis design

The construct reliability and validity of the measurement model within the TPB and NAM framework was initially examined. After reliability and validity issues were confirmed, our proposed hypotheses were evaluated individually before beginning the complete analysis of LGCM. Given that the SEM estimated via full information maximum likelihood (FIML) exhibited the nature of full-information analysis, all the hypotheses were reevaluated simultaneously at the end of the analysis when the trajectory pattern of repeated measures were already investigated during the analysis in the LGCM stage. Moreover, we introduced the application of BF to add information from the traditional p-value in testing hypotheses. BF calculation is explained in the next section.

Second, the trajectories of the participants' revisit intention were investigated using LGCM. The LGCM technique was selected to test our framework because it can be used to effectively and simultaneously examine fixed- and random-effects components. Moreover, other covariates can be introduced into the model to reflect individual differences due to LGCM's flexibility. Moreover, LGCM was performed from the perspective of traditional SEM, allowing it to control for measurement errors and provide traditional fit indices similar to the manner used by traditional SEM.

In our analysis, two latent variables extracted from the volunteer tourists' revisit intention, namely, latent intercept (i) and latent slope (s), facilitated our elaboration of linear and nonlinear relationships within our framework. In particular, the value of participant perception in the beginning can be translated from the mean latent intercept (μ_i), and the mean of the participant perception's rate change is represented by the latent slope (μ_s). In addition, individual differences expressed by the variance of the latent intercept (σ_i^2) and latent slope (σ_s^2) can be predicted by including explanatory variables, which are attitude, subjective norm, perceived behavioral control, and personal norm, in this case. Furthermore, the covariance between the latent intercept and latent slope ($\sigma_{i,s}$) indicates the overall movement pattern of each individual trajectory.

To evaluate the model fit of LGCM, we used the standardized root mean square residual (SRMR) and the comparative fit index (CFI) with values less than 0.08 for SRMR and greater than 0.95 for CFI as criteria for good fit (Hu & Bentler, 1999). However, we did not report the traditional root mean square error of approximation (RMSEA) due to the recent recommendation from Kenny, Kaniskan, and McCoach (2015), because the symptom of over-rejection by RMSEA prevails if the degree of freedom (*df*) is small (our maximum df in this study is 6).

Given that the focal analysis from LGCM is the unobserved latent trajectory factors and not the observation of repeated measures, we should conduct the subsequent analysis by focusing directly on repeated measures depending on the results of the LGCM analysis. If LGCM confirms the significance of the latent intercept and slope, then our analysis will rely on the direct effect of the predictor on a series of participants' revisit intention in Years 1, 3, and 5 (i) and the autoregressive (AR) process with a time lag between Years 1 and 3 and Years 3 and 5 (s). Moreover, TPB and NAM were incorporated into this model and tested to confirm the predictive ability of each theory and construct. This process was simultaneously performed using the traditional SEM framework.

Bayes factor (BF)

In the null hypothesis significance testing (NHST) paradigm, a measure of evidence to reject the null hypothesis is performed by the p-value, indicating that a smaller p-value induces a higher chance to reject the null hypothesis. That is, NHST is appropriate for lending support to the alternative hypothesis. In this regard, NHST never accepts the null hypothesis. Bayes factor (BF) has recently been recommended by scholars for hypothesis testing. BF can be regarded as an alternative method to NHST. In contrast with that of NHST, the interpretation of BF is easier. Table 2 summarizes the appropriate interpretation within every range of BF.

[Insert Table 2]

Computation of BF used in this study

H_0 denotes the null hypothesis, and H_1 denotes the alternative hypothesis. To test H_0 over H_1 given the observed raw data (RD), BF is computed as follows:

$$BF_{01} = \frac{P(RD|H_0)}{P(RD|H_1)}. \qquad (1)$$

According to equation (1), the main implication is that all the hypotheses must be correctly parameterized. In addition, all plausible cases of derived parameters must be used to determine each possibility that can be considered related to the hypotheses and then aggregated to obtain BF. This procedure implies the application of calculus, particularly the integrals ($\int$).Θ_i is the parameter spaces for H_i, and π_i is the prior probability density functions of the parameter spaces for H_i. Thus, we can express the continuous form of BF as follows:

$$BF_{01} = \frac{\int_{\theta \in \Theta_0} P(RD|H_0, \theta) \cdot \pi_0 \, d\theta}{\int_{\theta \in \Theta_1} P(RD|H_1, \theta) \cdot \pi_1 \, d\theta}. \quad (2)$$

However, closed-form solutions from using integrals in accordance with Equation (2) cannot be generally guaranteed. Hence, other methods to obtain BF should be explored.

Wagenmakers (2007) proposed an alternative method for approximating BF using the Bayesian information criterion (BIC). The proposed method can be summarized by the following relationship:

$$BIC(H_i) = -2 \cdot \log(L_i) + k_i \cdot \log(n),$$

where L_i denotes the maximum likelihood for model H_i, k_i represents the number of free parameters of model H_i, and n is the number of observations.

Through BIC, we can approximate BF in accordance with the following relation:

$$BF_{01} \approx \exp\left(\frac{1}{2} \cdot \partial BIC_{10}\right), \quad (3)$$

where ∂BIC_{10} = BIC(H_1) − BIC(H_0) or $\partial BIC_{10} = n\,(\log SSE_1 \cdot SSE_0^{-1}) + (k_1 - k_0)\log n$.

Therefore, our study calculated BF using Equation (3). With regard to the statistical software used throughout this analysis, the R programming version 3.6.1 with the "lavaan" (Rosseel, 2012), "semtools", "compute.es" (Del Re 2015), "MAd" (Del Re 2015), and "metafor" (Viechtbauer, 2010) packages was used to perform all the analyses in this study.

Results

Study 1: MASEM

We used a criterion recommended by Cohen (1988) to interpret different effect sizes: r^+ = 0.1 (small), r^+ = 0.3 (medium), and r^+ = 0.5 (large). As shown in Table 3, the mean of weighted correlation suggested that the relationship varied from medium (r^+ = 0.3) to large (r^+ = 0.57) effect sizes. In particular, attitude and personal norm exhibited the strongest relationship with behavioral intention (r^+ = 0.57). The association between subjective norm and behavioral intention was relatively strong (r^+ = 52) and stronger than that between perceived behavioral control and behavioral intention (r^+ = 45). In contrast to previous meta-analyses that posited that subjective norm is the weakest predictor of behavioral intention (Klöckner 2013, Sheppard, Hartwick, and Warshaw 1988), our meta-analysis showed that subjective norm is on par with attitude and personal norm. The difference among them was negligible. Similarly, the effect size between attitude and subjective norm was nearly large (r^+ = 0.43), and the association between the two norms was large (r^+ = 0.5). Heterogeneity statistics proved that the results of this study are reliable. In particular, i^2 varied from 75.931% to 97.33%. This result indicated an acceptable degree of true between-study heterogeneity. Moreover, the Fail-safe N, which is a statistical test used to examine the robustness of calculated effect sizes, exhibited acceptable ranges. The reported Fail-safe N was higher than the threshold level of $5k$ + 10. This finding proved that our mean of weighted correlation is robust.

[Insert Table 3]

Fig. 1 presents the standardized beta coefficients of MASEM. The most influential factor is subjective norm, which has a total effect of 0.474. Subsequently, attitude ($\beta_{ATB \to INT}$ = 0.32) and personal norm ($\beta_{PN \to INT}$ = 0.312) exert similar effects on intention, and the least effect is exhibited by perceived behavioral control ($\beta_{PN \to INT}$ = 0.45). Then, we generated the hierarchical analysis based on MASEM to perceive the real effect of introducing NAM into the original TPB. In the case of using the original TPB to predict behavioral intention, R^2 = 44%. In contrast with the original TPB, personal norm alone engendered R^2 = 32.5%. The difference of these explained variances was statistically significant (p-value of χ^2 < 0.000). Interestingly, when incorporating NAM after controlling for the original TPB, the explained variance increased to 48%. This finding implied that merging the original TPB with NAM can significantly enhance predictive power in the sustainable tourism context. In general, explained variance tends to increase when more variables are introduced into the model. The significance test is only effective for the case of the nested model. In addition, the p-value exhibits a limitation in model selection. Hence, BF was applied in this analysis to determine which model should be accepted. From the BF approximation (Wagenmakers 2007), we discovered a decisive evidence that favors the merged model (BF_{H1} > 100) over other choices. Fig. 1 presents the graphical illustration of MASEM.

[Insert Fig.1]

Subsequently, we simulated power analysis using MASEM as a population model. On the basis of Monte Carlo simulation with a sample size of 376, we estimated the relative bias, coverage ratio, and estimated power for our second study (volunteer tourism). With 50,000 rounds of simulation, the results showed that all the relative biases and coverage ratios are within the acceptable range in accordance with 376 observations. Similarly, power varied from 82.35% to 99%, falling into a highly satisfactory level. Therefore, we can ensure that with this sample size (n = 376), we can expect a power analysis greater than 82.35%. Table 4 summarizes our Monte Carlo simulation on MASEM with the estimated effect size (standardized beta coefficient).

[Insert Table 4]

Study 2: Empirical study (volunteer tourism)

Demographic profile:

The 376 respondents comprised 45% males and 55% females. In terms of age distribution, the minimum age was 20 years, the maximum age was 37 years, the average age was 23.85 years, and the standard deviation of age was 2.76. With regard to earnings, the most reported earning group was "$25,000–$39,999" (32%), followed by "Under $25,000" (30%), "$40,000–$54,999" (21%), and "$50,000 or higher" (17%). For educational level, the majority of the tourists held a bachelor's degree (78%), followed by a "two-year college degree" (14%), and "others" (3%).

Measurement model: First-order confirmatory factor analysis (CFA)

To evaluate the validity of the measurement model, we initially performed CFA on the sample data with 376 observations. In particular, our dataset violated the multivariate normal distribution as demonstrated by the significance in Mardia skewness ($p < 0.00$) and Mardia kurtosis ($p < 0.01$). Moreover, a univariate normality test suggested the clue of non-normal distribution due to the significance in the Shapirio–Wilk test in every indicator ($p < 0.01$). Our dataset has no missing data. Hence, the correction method of MLR is asymptotically equivalent to that of MLM (Rosseel 2010). In addition, the ML estimator with robust standard errors and robust test statistics for model evaluation (i.e., MLR) was used throughout this analysis. From the findings, the fit indices exhibited moderate fit with $\chi^2 = 183.449$, $df = 80$, $p < 0.05$, CFI = 0.967, Tucker–Lewis index (TLI) = 0.957, 90% confidence interval (CI) of RMSEA = [0.049 to 0.068], and SRMR = 0.049.

Construct reliability was evaluated based on average variance extracted (AVE) and composite reliability. The AVEs of all the constructs exceeded the threshold level of 0.5, as recommended by Fornell and Larcker (1981). The composite reliability calculated from all the constructs was higher than 0.7, as suggested by Hair, Howard, and Nitzl (2020). Therefore, sufficient pieces of evidence were obtained to conclude that the construct reliability values of all the measurement scales are within the satisfactory level.

We assessed construct validity through convergent validity and discriminant validity. All the standardized factor loadings are greater than 0.7, as suggested by Hair et al. (2020). Thus, convergent validity is clearly supported. On the basis of the concept of multitrait–multimethod (MTMM) correlations, the ratio of hetero-trait-mono-trait (HTMT) with the threshold that does not exceed 0.85 can be used as a criterion to confirm the evidence of discriminant validity (Henseler, Ringle, & Sarstedt, 2015). As suggested by Henseler et al. (2015), HTMT based on MTMM is more sensitive to a lack of discriminant validity than the traditional Fornell–Larker criteria. The findings showed that the computed HTMT ratios are less than 0.85, lending strong support to discriminant validity. The conventional discriminant validity and correlation matrix are also summarized in Table 5.

[Insert Table 5]

Hypothesis testing

Before the jointly hypothesized relationships were determined, we first evaluated each hypothesis separately to ensure that each factor had its own strength to be jointly used in testing the global framework. As reported in Table 6, all the proposed hypotheses (H1 to H6) were proven and supported using the NHST approach. Subsequently, we performed conventional SEM to assess model fit. We found that the fit indices indicated a moderate fit with χ^2 =

221.414, df = 83, p < 0.01, CFI = 0.948, TLI = 0.935, 90% RMSEA = 0.085, and SRMR = 0.083. However, our first hypothesis was rejected, indicating that attitude has no impact on intention to revisit in volunteer destination (β_{ATT} = −0.009, p = 0.874). By contrast, the other hypotheses were proven and supported. Our conclusion from the calculations of BF also supported the conclusion obtained from NHST. In particular, decisive pieces of evidence were found in favor of accepting the relationship between perceived behavioral control and intention (H3: BF_{H1} > 100), between subjective norm and attitude (H5: BF_{H1} > 100), and between subjective norm and personal norm (H6: BF_{H1} > 100). Moreover, we found extremely strong evidence that favored the relationship between subjective norm and intention (H2: BF_{H1} = 90.92). Nevertheless, BF suggested removing two hypotheses (H1 and H4). We found strong evidence to eliminate the relationship between attitude and intention (H1). However, we only detected ambiguous evidence suggesting the removal of the relationship between personal norm and intention (H4).

[Insert Table 6]

The contribution of NAM to TPB was assessed using BF and the traditional explained variance criteria. The results of the explained variance criteria indicated that without NAM, the explained variance determined by TPB accounted for 58.8%. However, incorporating NAM can explain 58.4%, which is less than 0.4% that of TPB. Similarly, BF supported the removal of NAM from TPB. However, BF_{H0} was 1.46, which lies within the ambiguous evidence category as shown in Table 2.

LGCM specification

Before investigating the effect of re-participation intention on each period, we first performed several nested unconditional LGCM to obtain the best fitting baseline model. During this stage, we compared three models, namely, an intercept-only model without a latent growth curve (Model 1), a linear growth model (Model 2), and a nonlinear growth curve model (Model 3). As recommended by Kline (2015), an empirical nonlinear trend can be investigated by fixing the first two coefficients of the latent slope to 0 and 1, and then freeing the remaining coefficients. This recommendation differs from the traditional nonlinear LGCM because the traditional method requires scholars to fit three latent factors: (1) latent intercept, (2) latent slope, and (3) latent quadratic. The method recommended by Kline (2015) is easier to fit because only two latent factors are required to be estimated, mitigating the risk of the non-convergence issue. Therefore, we fixed the latent factor's coefficients based on Kline's (2015) suggestion throughout the analysis stage. The results showed that the nonlinear growth curve model (i.e., baseline) exhibited the best fit.

[Insert Fig. 2]

As demonstrated in our baseline model (Fig. 1), LGCM with a nonlinear trend achieved good fit with the empirical data [$\chi^2(1)$ = 0.262, p = 0.609, CFI = 1, and SRMR = 0.004]. The findings indicated that the revisit intention of each participant initially had a mean of 4.401 (μ_i = 4.401, SE = 0.105, and p < 0.001) and averagely increased by 0.22 (μ_s = 0.22, SE = 0.057, and p < 0.001). Thus, the estimated average values of the revisit intention across Years 1, 3, and 5 were 4.401 (μ_{RI_1}), 4.621 (μ_{RI_2}), and 4.6837 (μ_{RI_3}), respectively.

From the analysis of BF interpreted in Table 2, we discovered decisive evidence for a negative association between the latent intercept and latent slope ($\sigma_{i,s}$= −0.532, SE = 0.124, p < 0.001, and BF_{H1} > 100). This finding implies that volunteers with a high level of revisit intention in Year 1 tend to significantly exhibit a decline in their level across time. By contrast, volunteers who have low level of revisit intention in the first year tend to dramatically exhibit an increase in their level across time. Moreover, we found a decisive evidence for individual differences when considering the variance of the baseline perception of revisit intention from each participant (σ_i = 3.839, SE = 0.206, p < 0.001, and BF_{H1} > 100) and their changes (σ_s = 0.88, SE = 0.229, p < 0.001, and BF_{H1} > 100).

Individual difference: Adding covariates

To discern the effect of individual difference on the trajectory of revisit intention, we regressed (1) demographic variables (Model 1), (2) re-participation intention (Model 2), (3) a set of variables in TPB (Model 3), (4) personal norm (Model 4), and (5) the integration of all the variables except for the demographic variables (Model 5).

[Insert Table 7]

As presented in Table 7, the results provided limited evidence for individual differences explaining the latent mean and latent slope of the trajectory in revisit intention across time. In particular, we found that age and gender variables barely exerted an effect on these latent factors. With regard to re-participation intention, we discovered a decisive evidence for a positive association of the baseline of revisit intention (β_{RPI} = 0.696, p < 0.000, BF_{H1} > 100). This finding implied that volunteer participants who had higher level of re-participation intention were positively associated with baseline revisit intention. However, re-participation intention had no effect on the change in the volunteer participants' revisit intention (β_{RPI} = 0.018 and p < 0.766). This finding is in line with the results from BF, indicating that strong pieces of evidence are available to support our model without the existence of a relationship between re-participation intention and latent slope (BF_{H0} = 18.57).

In examining the three variables of TPB, we found strong evidence that attitude was not associated with the baseline of revisit intention (β_{ATT} = −0.043, p = 0.397, and BF_{H0} = 14.51) and the growth in the volunteer participants' revisit intention (β_{ATT} = 0.088, p = 0.138, and BF_{H0} = 10). However, we found a decisive evidence to prove a positive association between subjective norm and the baseline of revisit intention (β_{SN} = 0.488, $p < 0.001$, BF_{H1} > 100). We also found substantial evidence to support a negative association between subjective norm and change in the volunteer participation's revisit intention (β_{SN} = −0.151, p = 0.024, and BF_{H0} = 3.28). Moreover, we detected substantial evidence to support a positive association between perceived behavioral control and the baseline revisit intention (β_{PBC} = 0.236, $p < 0.001$, and BF_{H1} = 6.93). By contrast, no relationship was found between perceived behavioral control and change in revisit intention (β_{PBC} = −0.005 and p = 0.945). These findings are in line with the results using BF, wherein decisive evidence was found to support our model without the existence of the relationship between perceived behavioral control and the growth in the revisit intention of volunteer participants (BF_{H0} > 100).

For the case of personal norm, we detected decisive pieces of evidence to support the association between personal norm and the baseline revisit intention (β_{PN} = 0.461, $p < 0.001$, and BF_{H1} > 100). However, we discovered substantial evidence to support our model without the existence of a relationship between personal norm and the growth in revisit intention (β_{PN} = −0.079, p = 0.238, and BF_{H0} = 8.83). The fifth model integrates both TPB and NAM into revisit intention to explain the three timeframes of revisit intention. attitude and perceived behavioral control cannot explain the latent intercept and latent slope. personal norm and revisit intention can only explain the latent intercept. Only subjective norm can predict both the latent intercept and latent slope.

In summary, unconditional LGCM indicates that the latent intercept and latent slope provide decisive evidence for explaining the trajectory of revisit intention. However, when introducing more covariates into the model, only subjective norm can predict both latent factors. This finding implies that using an AR process and allowing revisit intention to explain each time frame are better. Hence, the subsequent analysis re-specifies the SEM with AR process.

Revisited SEM with AR process

In this section, we re-specify the conceptual framework based on the LGCM result. All the hypotheses tested separately in Section 4.2.2 were jointly tested, as shown in Table 7 (Model 6 column). Only the first hypothesis was rejected ($\beta_{ATT} = -0.027$, $p = 0.438$, and $BF_{H0} > 100$). From the findings, the fit indices indicated a moderate fit with $\chi^2 = 643.319$, $df = 139$, $p < 0.01$, CFI = 0.915, TLI = 0.906, and RMSEA = 0.098. Fig. 3 presents the graphical illustration of the SEM with AR(1) process.

[Insert Fig.3]

Model 7 is our re-specified model with the AR process. The findings indicated that the fit indices exhibited an acceptable fit with $\chi^2 = 403.877$, $df = 125$, $p < 0.01$, CFI = 0.953, TLI = 0.942, and RMSEA = 0.077. Explaining each time frame with the overall revisit intention also exhibited a temporal distance decay effect. That is, the highest impact is on one-year revisit intention ($\beta_{INT \to RI_1} = 0.677$), the moderate impact is on three-year revisit intention ($\beta_{INT \to RI_3} = 0.244$), and the lowest impact is on five-year revisit intention ($\beta_{INT \to RI_5} = 0.106$). These findings implied that most participants put more weight on the one-year time frame when encountering the question without time scope. However, the revisit intention of the future period is a function of the past ($\beta_{RI_1 \rightarrow RI_3}$ = 0.655 and $\beta_{RI_3 \rightarrow RI_5}$ = 0.874).

Discussion and implication

Consistent with the call for additional research on volunteer tourism topics, this work addresses the emerging significance of studying the formation of revisit intention, particularly among youth tourists, under this topic. We ensure the robustness of our findings by considering macro and micro studies. To achieve our first objective, the methodology used to investigate this gap begins by drawing a macro conclusion about the usability of the merged theory by using the meta-analysis technique based on previous prosocial or pro-environmental studies as a representative of volunteer tourism. Then, the examination of the merged theory on volunteer tourism is tested. This research advances the volunteer tourism literature by extending the analysis to cover the identification of tourist type using the latent growth curve paradigm. The discussions pertaining to our study are as follows.

In accordance with the agreement by researchers that the impact of the factors within TPB varied in different contexts (Ajzen 1991), Table 8 shows the association of each factor with behavioral intention for consideration in different settings, such as general intention (Armitage & Conner, 2001) or pro-social/pro-environmental intention (Bamberg & Möser, 2007; Han & Stoel, 2017). The range of the weighted mean correlation effect size's magnitudes was rated from medium to strong. This result is consistent with previous findings (Bamberg & Möser, 2007). As expected, attitude (r^+ = 0.56) and personal norm (r^+ = 0.56) had the strongest effect sizes reported by the correlation coefficients. These values are in line with the prior meta-analytic literature shown by Armitage and Conner (2001) (r^+_{ATB} = 0.49), Bamberg and Möser (2007) (r^+_{ATB} = 0.62 and r^+_{PN}= 0.59), and Han and Stoel (2017) (r^+_{ATB} = 0.53). However, the effect size of subjective norm was reported to be strong (r^+ = 0.56) and in par with that of attitude/personal norm, with a negligible difference. This result considerably differs from those of previous studies, which argued that subjective norm is the weakest driver (Sheppard et al., 1988). However, when compared with the meta-analysis result conducted by Han and Stoel (2017), the effect sizes of attitude–intention and subjective norm–intention are on par and close to our results. Other meta-analytic studies might have examined behavioral intention in the general context, while our study and that of Han and Stoel (2017) concentrated on socially responsible consumers' behavioral intention. Moreover, we also found that subjective norm can trigger intention through attitude (r^+ = 0.43). These findings are also consistent with previous studies that highlighted the importance of subjective norm or social norm in pro-social behavior (Schultz, Khazian, & Zaleski, 2008). Therefore, enhancing tourists' intention through the channel of subjective norm can be an effective tool for practitioners. Furthermore, perceived behavioral control was reported to have a medium effect size (r^+ = 0.47). Compared with the results of previous studies, this variable exhibits a high variation. Bamberg and Möser (2007) reported that the effect size of perceived behavioral control–intention was high (r^+ = 0.54); by contrast, Han and Stoel (2017) reported a medium level (r^+ = 0.39). However, perceived behavioral control–intention for hotel/tourism services, particularly for Asian consumers, was reported to exhibit a medium effect size (r^+ = 0.47), which is consistent with our result. The difference in the strength of effect sizes across studies can be attributed to the different contexts of various studies.

[Insert Table 8]

[Insert Table 9]

MASEM confirmed that the total impact of subjective norm on intention is the strongest ($\beta_{SN \to INT}$ = 0.469) in the pro-social/pro-environment context, as shown in Table 9. This result contradicted the prior MASEM, which indicated that subjective norm exhibited no relationship with intention ($\beta_{SN \to INT}$ = 0.065) (Bamberg & Möser, 2007). The effects of attitude and personal norm on intention from our MASEM are consistent with other MASEM. Similarly, the effects of subjective norm on attitude and personal norm are in line with previous MASEM studies. However, the effects of perceived behavioral control on intention varied across studies. Fig. 4 shows the graphical illustration of the updated and previous MASEM studies.

[Insert Fig.4]

Our study updated and retested the marginal contribution of introducing NAM to the traditional TPB to explicate tourists' intention. The findings from the updated MASEM exhibited that the TPB (44.5%) and NAM (31.4%) frameworks achieved highly satisfactory performance levels in explaining behavioral intention within the scope of pro-social or pro-environment tourism. By merging the two theories, the explained variance was enhanced to 48%. Such findings are consistent with those of the prior meta-analytic literature. That is, predictive power was significantly increased when researchers incorporated personal norm (moral obligation or moral norm) into the original TPB (Han & Stoel, 2017). Prior meta-analytic studies arrived at a similar conclusion. For example, Han and Stoel (2017) collected 30 independent studies to test the contribution of NAM to TPB in the context of general social consumer behavior. After accounting for the effect of TPB, moral norm contributed approximately 2% to the additional explained variance. Evidently, the inclusion of personal norm is recommended to merge with the conventional TPB construct to improve predictive power in forecasting tourists' behavioral intention in pro-social or pro-environmental studies.

Moreover, social norm is believed to be a powerful factor that can activate personal norm [current study $\beta_{SN \rightarrow PN}$ = 0.5 and Bamberg and Möser (2007) $\beta_{SN \rightarrow PN}$ = 0.53], which is similar to the prior literature (Warner & Joynt, 2002). Therefore, researchers are encouraged to consider personal norm a mediator between social norm and behavioral intention.

This study tested the predictive power of the merged TPB and NAM in the context of volunteer tourism. The results from the hypothesis testing indicated that all the hypotheses (H1 to H6) were supported in the case of separate testing, implying that each variable exerts a crucial effect on revisit intention. However, the impact of attitude on revisit intention (H1) was rejected (β_{ATB} = −0.027) when the hypotheses were collectively tested. Meanwhile, the impact of subjective norm on revisit intention is the most apparent (β_{SN} = 0.417). As mentioned earlier, the meta-analytic literature suggests that subjective norm is the weakest predictor (e.g., Godin & Kok, 1996) in the general context. By contrast, meta-analytic studies in the pro-social context support the perception that subjective norm is the critical predictor of tourists' behavioral intention (Bamberg & Möser, 2007). Another issue that should be discussed is the insignificant impact of attitude on revisit intention. Such finding contradicts our hypothesis and those of other studies. A large body of literature in sustainable tourism has provided support for the positive impact of attitude on behavioral intention (Han, Hsu, & Lee, 2009; Han, Hsu, Lee, & Sheu, 2011; Han et al., 2010; Han, Hwang, Lee, & Kim, 2019). Although the empirical finding contradicts our hypothesis and those of the previous literature, the result of our study is still in line with that from Lee and Lina Kim (2018), who investigated volunteer tourists' intended participation via TPB. They found that attitude exerts an insignificant impact on tourists' intention to participate (β_{ATB} = 0.03 and p-value = 0.45). The possible reason is that the context of volunteer tourism significantly differs from other sustainable tourism contexts. Volunteer tourism can be classified as a micro niche market (Han, Meng, et al., 2019), and thus, has a limited choice in tourists' perspective compared with general tourism type. With the limited supply of volunteer destinations, the impact of perceived behavioral control is strengthened (Han & Stoel, 2017). In addition, if the participants' peer group favors a person who positively contribute to the society or community, tourists who previously do not have a positive attitude to participate in volunteer tourism may intend to join volunteer activities to gain the approval of their peer group. In such situation, perceived behavioral control (β_{PBC} = 0.342) and subjective norm (β_{SN} = 0.417) are considered two key drivers for triggering tourists' intention to join such volunteer activities. Tourists can partake in such activities without a positive attitude toward participation ($\beta_{ATB} = -0.27$).

In addition, our study addressed the possibility of fluctuation of revisit intention across time by introducing the latent growth curve analysis in the second study based on the volunteer tourism. Our results from SEM with the AR process (Model 7 in Table 7) also indicated that the fit indices of the overall model (χ^2 = 403.877, df = 125, $p < 0.01$, CFI = 0.953, TLI = 0.942, and RMSEA = 0.077) is better than those of the model without the AR process (Model 6: χ^2 = 643.319, df = 139, $p < 0.01$, CFI = 0.915, TLI = 0.906, and RMSEA = 0.098). Researchers are recommended to extend revisit intention when investigating TPB or NAM in predicting tourists' intention in the volunteer tourism context. Another point is that the effect of the overall revisit intention on each period exhibited decaying effects ($\beta_{RI \to RI_1}$= 0.677, $\beta_{RI \to RI_3}$= 0.244, and $\beta_{RI \to RI_5}$= 0.106). However, the effect of revisit intention on each period can be used effectively to forecast future intention ($\beta_{RI_1 \to RI_3}$ = 0.655 and $\beta_{RI_3 \to RI_5}$ = 0.874). These findings are important points to consider because destination managers can manage and maintain the level of revisit intention in each period by continuously stimulating tourists' demand to revisit the destination. Our research provides implications in terms of methodology, theory, and practicality based on the preceding empirical findings.

Methodological implications

The use of the p-value in null hypothesis significance testing is a common practice among tourism scholars. However, such practice has been challenged by an alternative procedure, called the Bayes factor, which exhibits robustness and interpretability (Assaf, Tsionas, & Oh, 2018). Moreover, studies that used the Bayes factor to test empirical hypotheses in tourism remain scarce. The methodological contribution of the current study is to improve the robustness and validity of findings by applying the Bayes factor procedure in accordance with the traditional p-value.

[Insert Table 10]

In general, tourism scholars tend to depend on the rule of thumb (10×) or power analysis applications (e.g., G*power) when determining the appropriateness of sample size. Some of these practices (e.g., rule of thumb) have been recently criticized by methodologists (Benitez, Henseler, Castillo, & Schuberth, 2020). Considering the advantages of MASEM, we updated the new information extracted from volunteer tourism in this study to the MASEM database. Methodologically, we contribute to future prosocial and volunteer tourism research by generating a plausible set of recommended minimum sample sizes for scholars to achieve a triggered statistical power level, as shown in Table 10.

Theoretical implications

Our research is the first attempt in volunteer tourism to draw a macro conclusion of the predictive power produced by the merging of TPB and NAM from the meta-analysis perspective. The findings indicate that the introduction of NAM into TPB marginally enhances the variance explained by the overall model. Existing studies on volunteer tourism have focused on using only TPB (Lee & Lina Kim, 2018; Meng et al., 2020), which considers only the self-interest motive (Shin et al., 2018), to predict behavioral intention. However, volunteer tourism, as a form of sustainable tourism, exhibits a unique characteristic in which the prosocial motive plays a critical role in driving participants to overcome burdens during volunteer activities. Hence, the current study contributes to theoretical development by providing the missing aspect required for explaining revisit intention in the case of youth volunteer tourism to cover self-interest and prosocial motives by introducing NAM into the original TPB framework.

The most significant theoretical contribution of this study is probably the discovery of the mediating role of personal norm activated by triggering subjective or social norms in shaping favorable revisit intention in a general prosocial behavioral context, including volunteer tourism. The previous literature tends to separately investigate the effects of subjective and personal norms in general behavioral study and assumes that their effects are similar to those in prosocial behavioral study. However, this missing link is underexplored when scholars extend their interest to volunteer tourism. The current research fills this void by verifying the significant role of personal norms in transmitting the effects of subjective norms to revisit intention. Another implication of this outcome is that subjective norm is the major driving force, directly and indirectly, and thus, it influences revisit intention in prosocial behavior, particularly in youth volunteer tourism. Consequently, this research enriches behavioral study in the volunteer tourism literature by clarifying the underexplored link between subjective and personal norms.

Practical implications

This study provides several practical implications. In contrast with previous research that highlights the salient effect of attitude on behavioral intention, the results of the current meta-analysis and empirical volunteer tourism confirm the imperative role of subjective norm in enhancing revisit intention. On the basis of this result, practitioners should focus on stimulating volunteer participants to develop their intention to revisit a destination via subjective norm. The major benefit of focusing on this aspect is that subjective norm directly affects the behavioral intention of tourists and can also help activate their personal norm, and thus, engender their intention to revisit the same destination. In particular, posting a set of attractive pictures online (e.g., on Facebook, Instagram, or other social media) that portray the happiness of a community or the smiling faces of people who received help from volunteers can activate the moral norm of potential tourists. Providing a free space to share opinions from important and recognized people or celebrities in a creative manner is also helpful in gradually shaping members' value within a community. Practitioners can anticipate the enhancement of the moral norms and positive attitude of potential volunteer tourists by focusing on improving subjective norm or social pressure.

Moreover, the knowledge synthesized from the temporal effect of revisit intention based on LGCM can help practitioners understand their potential customers. In accordance with the trichotomous tourist segmentation (Feng & Jang, 2004; Jang & Feng, 2007), youth travelers are identified as deferred repeaters in our study. These travelers exhibit low short-term revisit intention but high long-term revisit intention. Previous empirical evidence supports that tourists in the youth segment are classified as potential switchers who tend to visit a nearby destination after their exploration (Jang & Feng, 2007). As implied by the previous literature (Gyte & Phelps, 1989), the most influential driver for deferred repeaters is novelty. This finding is highly informative to destination marketing organizations when preparing an appropriate strategy for dealing with deferred repeaters by rejuvenating a destination in terms of experience or physical attraction to draw novelty-seeking travelers.

Limitation and future research

Several limitations are inherent in this literature. First, the findings from MASEM that are limited with small number of sample size (23 studies) can yield inaccurate results. This limitation is partly due to insufficient information reported in the articles. Several articles were removed because they did not provide relevant effect sizes that naturally fitted with MASEM although some effect sizes can be estimated from the insufficient information within those articles. Future research should provide at least all pairs of correlation coefficients and the number of observations. Apart from the sufficiency of reported information, the integrated model should be encouraged to test in various destinations. The results of our MASEM indicated that social norm is a key driver in engendering tourists' intention. Our empirical research seems to strengthen the aforementioned argument because such effect is the strongest. However, the research was conducted in South Korea, where culture is inherently distinguished from that of the West. Culture can be perceived as social glue that can shape people's attitudes, values, and norms (Warner and Joynt 2002). The conclusions can be different if this research is conducted in Western countries. Hence, although the results of MASEM can be generalized in the context of general pro-social and pro-environmental intention, generalizability is limited in the case of volunteer tourism.

A series of meta-analytic reviews highlighted a strong correlation between behavioral intention and real behavior (Sheppard, Hartwick, and Warshaw 1988, Ouellette and Wood 1998). Although behavioral intention can be used to approximate actual behavior (Shim et al. 2001), behavioral intention is not real behavior. To close the gap between the two concepts, future research should search for the missing link. Given that our temporal effect's result implies that our tourist typology in volunteer tourism can be deferred as repeaters and continuous switchers, future research should consider adding relative choice items (e.g., other destinations) and a novelty aspect into the questionnaire to more accurately reflect intention. This literature gathered cross-sectional data. Thus, the implication from such study is the association among the constructs instead of a causal relationship. Future research should focus on an experimental study based on randomization to draw a causal relationship conclusion. Another means of establishing a causal relationship is to conduct a longitudinal study in future research. Hence, volunteer tourism based on this extended framework is encouraged to be conducted in different contexts.

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[Insert Appendix]

Fig. 1. Graphical Summary of meta-analysis structural equation modeling

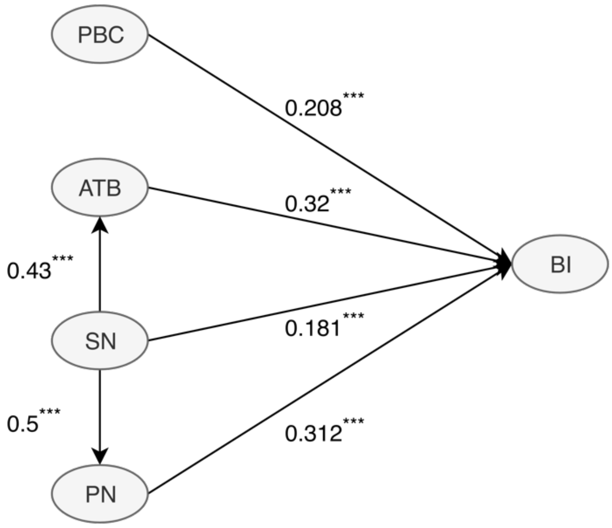


Fig. 2. Graphical illustration of Latent Growth Curve Analysis of volunteer revisit intention

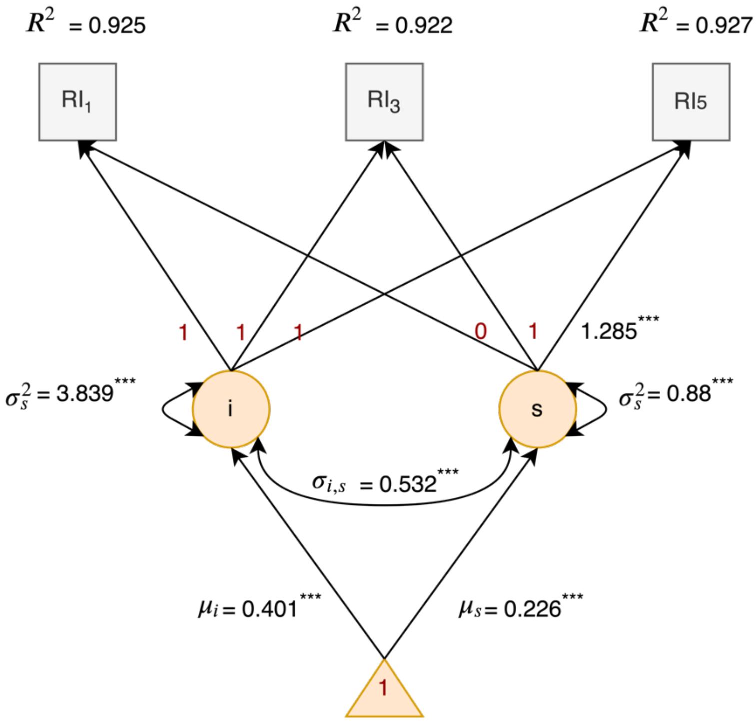
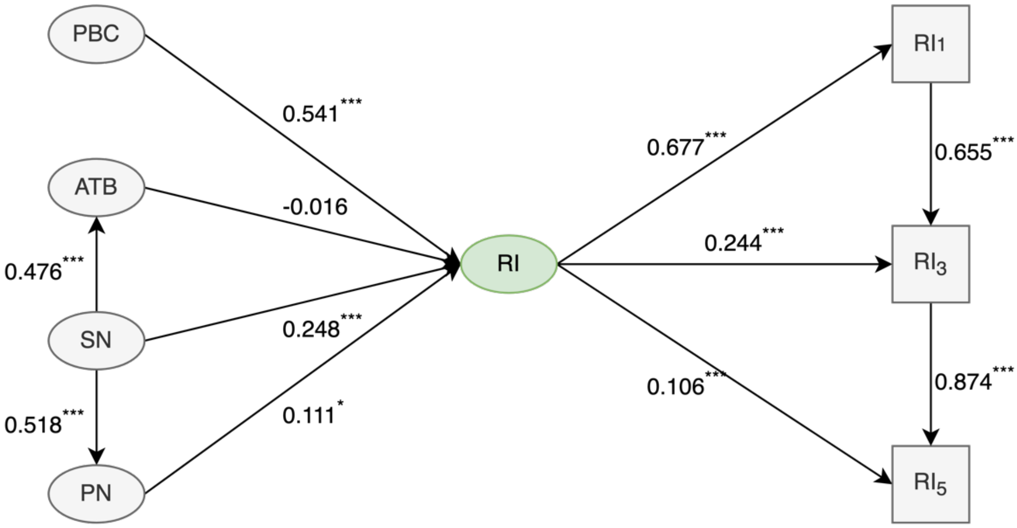


Fig. 3. Graphical illustration of SEM with AR (1) process



χ^2 = 403.877
df = 125

Fit indices:
RMSEA = 0.077, SRMR = 0.082, CFI = 0.953, TLI = 0.942, BIC = 19385.263

Fig. 4. Graphical illustration of MASEM compared with Bamberg and Möser (2007)

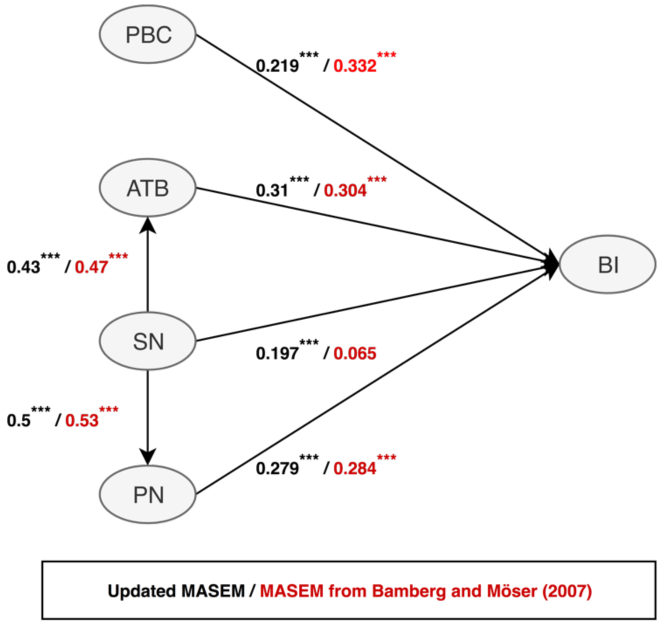


Table 1. Reported correlation coefficient selected from SSCI's relevant articles to use in MASEM

					Reported correlation coefficient value between construct from the literature									
No	**Author(s)**	**Context**	**Journal**	**N**	**ATB:SN**	**ATB:PBC**	**ATB:PN**	**ATB:INT**	**SN:PBC**	**SN:PN**	**SN:INT**	**PBC:PN**	**PBC:INT**	**PN:INT**
1	Ahn and Kwon (2019)	Green hotel	CIT	326	na	na	na	0.76	na	na	na	na	na	na
2	Chen and Tung (2014)	Green hotel	IJHM	559	0.35	0.34	0.33	0.5	0.36	0.21	0.52	0.37	0.57	0.37
3	Garay et al. (2019)	Water saving	JTR	284	0.386	0.442	na	0.467	0.51	na	0.678	na	0.597	na
4	H. Han (2015)	Green lodging	TM	308	0.501	0.498	0.506	0.62	0.316	0.527	0.559	0.243	0.436	0.588
5	H. Han et al. (2010)	Green hotel	TM	428	0.487	0.256	na	0.645	0.229	na	0.585	na	0.45	na
6	H. Han and Hyun (2017)	Green museum	JTTM	429	0.4	0.45	0.39	0.52	0.41	0.45	0.45	0.37	0.45	0.56
7	H. Han and Kim (2010)	Green hotel	IJHM	434	0.498	0.273	na	0.669	0.233	na	0.638	na	0.465	na
8	H. Han, Meng, and Kim (2017)	Bicycle tourism	JST	394	0.16	0.28	0.19	0.43	0.38	0.27	0.43	0.19	0.43	0.28
9	H. Han and Yoon (2015)	Eco-friendly hotel	JST	300	0.353	0.658	na	0.673	0.299	na	0.376	na	0.714	na
10	H. Han et al. (2019)	Eco-cruises	TM	350	0.408	na	0.507	0.536	na	0.716	0.709	na	na	0.808
11	H. Han, Lee, et al. (2019)	Eco-friendly airplane	IJHM	280	na	na	na	na	na	0.674	0.529	na	0.657	na
12	Juschten et al. (2019)	Destination choice: Alpine	TM	877	0.47	0.15	na	0.36	0.43	na	0.56	na	0.43	na
13	Kiatkawsin and Han (2017)	Pro-environmental behavior	TM	538	na	na	na	na	na	na	na	na	na	0.663
14	Y. Kim and Han (2010)	Green hotel	JST	389	0.179	0.126	na	0.487	0.059	na	0.162	na	0.194	na
15	Y. G. Kim et al. (2018)	Sharing economy	IJHM	344	0.504	0.444	na	0.679	0.259	na	0.496	na	0.422	na
16	Lee and Lina Kim (2018)	Volunteer tourism	IJTR	487	na	na	na	0.0894	na	na	0.3066	na	0.565	na
17	Li and Wu (2019)	Pro-environmental behavior	JDMM	554	0.46	0.43	0.46	0.39	0.44	na	na	na	na	na
18	Poudel and Nyaupane (2017)	Environmental concern	TPD	230	na	na	na	0.5657	na	na	0.4797	na	0.4	na
19	Teng et al. (2015)	Green hotel	JHTR	258	0.5	0.102	na	0.529	0.129	na	0.504	na	0.174	na
20	Untaru et al. (2016)	Environmental concern	IJHM	354	0.24	0.198	na	0.655	0.27	na	0.304	na	0.35	na
21	Vesci (2019)	Festival quality	JHTM	695	0.491	0.113	na	0.759	0.099	na	0.574	na	0.034	na
22	J. Wang et al. (2018)	Green hotel	IJCHM	324	0.71	0.52	na	0.73	0.56	na	0.73	na	0.59	na
23	This study	Volunteer tourism		376	0.463	0.419	0.476	0.336	0.541	0.507	0.624	0.596	0.651	0.491

na = correlation coefficient is not reported in the literature

CIT = Current Issues of Tourism; IJCHM = International Journal of Contemporary Hospitality Management; JTR = Journal of Travel Research; TM = Tourism Management; JTTM = Journal of Travel and Tourism Marketing; IJHM = International Journal of Hospitality Management; JST = Journal of Sustainable Tourism; IJTR = International Journal of Tourism Research; JDMM = Journal of Destination and Marketing Management; TPD = Tourism Planning and Development

Table 2. Bayes Factor interpretation

Bayes Factor	Interpretation
Greater than 100	Decisive evidence
30 – 100	Very strong evidence
10 – 30	Strong evidence
3 – 10	Substantial evidence
1 – 3	Ambiguous evidence
1	No evidence

Adapted from Wetzels and Wagenmakers (2012)

Table 3. Summary of calculated meta-analysis effect sizes

Effect size	k	n	$r^+_{R.E.}$	$r^+_{95\%\,CI}$	τ^2	i^2 (%)	h^2	Fail-safe N
ATB-SN	17	7281	0.43	[0.36, 0.49]	0.026	91.649	11.9746	9173
ATB-PBC	16	6931	0.34	[0.25, 0.42]	0.0362	93.9145	16.4326	4590
ATB-PN	6	2594	0.4	[0.30, 0.49]	0.0175	88.147	8.4367	1002
ATB-INT	6	2594	0.57	[0.47, 0.61]	0.0495	95.3042	21.2956	24176
SN-PBC	16	6931	0.32	[0.25, 0.39]	0.0235	90.907	10.9974	4290
SN-PN	6	2320	0.5	[0.31, 0.65]	0.0749	96.6017	29.4267	1375
SN-INT	19	7724	0.52	[0.41, 0.55]	0.0361	93.5214	15.4354	17148
PBC-PN	4	1690	0.3	[0.21, 0.38]	0.0076	75.9311	4.1547	233
PBC-INT	18	7374	0.45	[0.37, 0.53]	0.0438	94.6403	18.6578	10914
PN-INT	6	2578	0.57	[0.39, 0.71]	0.0862	97.33	37.4536	2303

Note: $r^+_{R.E.}$ = meta correlation coefficient with random effects; $r^+_{95\%\,CI}$ = 95% confidence interval of meta correlation coefficient τ^2 = the heterogeneity variance that has to be estimated, which is equivalence to $Var(u_i)$; i^2 (%) = the degree of heterogeneity of effect sizes: In our analysis, we followed the Higgins and Thompson (2002) procedure to interpret it as the proportion of the total variation of the effect size that is due to the between study heterogeneity; h^2 = the degree of heterogeneity (squared estimated residual standard deviation from the slope of the un-weighted least squares regression line)

Table 4: Power analysis based on MASEM with standardized beta coefficients (n = 376)

Relationship	Relative bias	Relative SE bias	Coverage	Power	MASEM*
$ATB \rightarrow INT$	-0.00519	-0.01218	0.9483	0.9998	0.320***
$SN \rightarrow INT$	-0.00123	-0.01659	0.9465	0.8235	0.181***
$PBC \rightarrow INT$	0.00076	-0.01134	0.9467	0.9969	0.208***
$PN \rightarrow INT$	-0.00441	-0.01777	0.9445	0.9999	0.312***
$SN \rightarrow ATB$	-0.00418	-0.00808	0.9495	0.9999	0.430***
$SN \rightarrow PN$	-0.00456	-0.01830	0.9460	0.9999	0.500***

MASEM* = Standardized beta coefficient calculated from the correlation matrix's MASEM
Note: This Monte Carlo simulation simulate 50,000 samples (datasets) from a population with known parameter value, which is generated from the MASEM. Later on, for each of the samples, the parameters of interest are calculated with the standard errors and then averaged over all those samples.

Table 5: Discriminant validity: Traditional criteria and HTMT ratio of correlations

	ATB	SN	PBC	PN	INT	RI1	RI3	RI5
ATB	**0.849**	0.463	0.419	0.476	0.336	-	-	-
SN	0.476	**0.912**	0.541	0.507	0.624	-	-	-
PBC	0.304	0.638	**0.748**	0.596	0.651	-	-	-
PN	0.247	0.518	0.330	**0.846**	0.491	-	-	-
INT	0.293	0.643	0.731	0.414	**0.935**	-	-	-
RI1	0.199	0.435	0.495	0.281	0.677	-	-	-
RI3	0.202	0.442	0.502	0.285	0.687	0.820	-	-
RI5	0.200	0.438	0.498	0.282	0.681	0.751	0.916	-

Note: The bold diagonal values are the square root of the AVE. Lower triangle elements are the correlation coefficient between constructs. Upper off-diagonal elements are the HTMT ratio, which is calculated using $\frac{\frac{1}{K_iK_j}\sum_{g=1}^{K_i}\sum_{h=1}^{K_j}r_{ig,jh}}{\sqrt{\frac{2}{K_i(K_1-1)}\sum_{g=1}^{K_i-1}\sum_{h=g+1}^{K_i}r_{ig,jh}\frac{2}{K_j(K_j-1)}\sum_{g=1}^{K_j-1}\sum_{h=g+1}^{K_j}r_{jg,jh}}}$ **based on recommendation from Henseler, Ringle, and Sarstedt (2015)**

Table 6: Results from hypothesis testing and the Bayes factor

		Separately analyzed		Jointly analyzed		Decision based on Bayes Factor		
Hypothesis	Relationship	Standardized Beta	Result	Standardized Beta	Result	Bayes Factor	Decision	Interpretation
H1	$ATB \rightarrow INT$	0.360***	Fail to reject	-0.009	Reject	19.10 (BF_0)	Favor remove	Strong evidence
H2	$SN \rightarrow INT$	0.618***	Fail to reject	0.236***	Fail to reject	90.92 (BF_1)	Favor retain	Very strong evidence
H3	$PBC \rightarrow INT$	0.740***	Fail to reject	0.541***	Fail to reject	1.2×10^{15} (BF_1)	Favor retain	Decisive evidence
H4	$PN \rightarrow INT$	0.484***	Fail to reject	0.108*	Fail to reject	1.75 (BF_0)	Favor remove	Ambiguous evidence
H5	$SN \rightarrow ATB$	0.458***	Fail to reject	0.476***	Fail to reject	$7.3\ x10^{19}$ (BF_1)	Favor retain	Decisive evidence
H6	$SN \rightarrow PN$	0.496***	Fail to reject	0.518***	Fail to reject	$9.4\ x10^{19}$ (BF_1)	Favor retain	Decisive evidence

***** $p < 0.001$; ** $p < 0.05$; * $p < 0.1$**

BF_0 = Bayes factor with favor of the alternative hypothesis; BF_1 = Bayes factor with favor of the null hypothesis.

Table 7: Summary of key parameters in LGCM and SEM

Parameters:	Baseline	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
i	4.401***	5.544***	0.293	-1.208	-0.413	-0.639	0.224	
s	0.226***	0.876	0.176	0.188	0.62	0.361	0.226 (f)	
$cov(i,s)$	-0.532***	-0.546***	-0.545***	-0.427***	-0.477***	-0.505***	-0.537***	
Age $\rightarrow i$		-.076						
Gender $\rightarrow i$		0.025						
Age $\rightarrow s$		-0.093						
Gender $\rightarrow s$		0.039						
$INT \rightarrow i$			0.696***				0.703***	
$INT \rightarrow s$			0.018				0.002	
$ATB \rightarrow i$				-0.043				
$ATB \rightarrow s$				0.088				
$SN \rightarrow i$				0.488***				
$SN \rightarrow s$				-0.151*				
$PBC \rightarrow i$				0.236***				
$PBC \rightarrow s$				-0.005				
$PN \rightarrow i$					0.461***			
$PN \rightarrow s$					-0.079			
$INT \rightarrow i$						0.5***		
$INT \rightarrow s$						0.181		
$ATB \rightarrow i$						-0.077		
$ATB \rightarrow s$						0.107		
$SN \rightarrow i$						0.244***		
$SN \rightarrow s$						-0.214*		
$PBC \rightarrow i$						0.003		
$PBC \rightarrow s$						-0.046		
$PN \rightarrow i$						0.122*		
$PN \rightarrow s$						-0.078		
$RI_1 \rightarrow RI_3$								0.655***
$RI_3 \rightarrow RI_5$								0..874***
$INT \rightarrow RI_1$								0.677***
$INT \rightarrow RI_3$								0.244***
$INT \rightarrow RI_5$								0.106***
$ATB \rightarrow INT$							-0.027	-0.016
$SN \rightarrow INT$							0.417***	0.248***
$PBC \rightarrow INT$							0.342***	0.541***
$PN \rightarrow INT$							0.124*	0.111*
$SN \rightarrow ATB$							0.481***	0.476***
$SN \rightarrow PN$							0.521***	0.518***
Fit indices:								
$\chi^2(df)$	0.227 (1)	1.356 (4)	34.731 (11)	348.402 (54)	22.66 (12)	614.403 (130)	643.319 (139)	403.877 (125)
$p\ (\chi^2)$	0.634	0.852	0.000	0.000	0.031	0.000	0.000	0.000
RMSEA	0.000	0.000	0.076	0.120	0.049	0.1	0.098	0.077
SRMR	0.004	0.004	0.037	0.136	0.033	0.129	0.133	0.082
CFI	0.994	1	0.991	0.914	0.994	0.918	0.915	0.953
TLI	0.999	1.005	0.987	0.895	0.993	0.903	0.906	0.942
BIC	3734.428	3745.56	6892.144	13519.603	6800.464	19672.874	19648.423	19385.263

***** $p < 0.001$**
**** $p < 0.01$**
*** $p < 0.05$**
i = latent intercept; s = latent slope; INT = Revisit intention; RI_1 = Revisit intention within 12 months; RI_3 = Revisit intention within year 3; RI_5 = Revisit intention within 5 years; (f) = fixed parameters (e.g., slope) to the same values from those reported in baseline model; $p\ (\chi^2)$ = probability of Chi-square; RMSEA = Root Mean Square Error of Approximation; SRMR = Standardized Root Mean Square Residual; CFI = Comparative Fit Index; TLI = Tucker-Lewis Index; BIC = Bayesian Information Criterion

Table 8: Updated meta-correlation compared with the previous reviews

Relationship	AC (2001)	BM (2007)	HS (2017)	MASEM*	Updated MASEM**
ATB-SN	np	0.47	0.44	0.43	0.43
ATB-PBC	np	0.44	np	0.34	0.34
ATB-PN	np	0.67	np	0.4	0.38
ATB-INT	0.49	0.62	0.53	0.57	0.56
SN-PBC	np	0.29	np	0.32	0.34
SN-PN	np	0.53	np	0.5	0.50
SN-INT	0.34	0.42	0.50	0.52	0.52
PBC-PN	np	0.35	np	0.30	0.30
PBC-INT	np	0.54	0.39	0.45	0.47
PN-INT	np	0.59	np	0.57	0.55

MASEM* = Meta-correlation from the first study; Updated MASEM = Meta-correlation after updating the results from volunteer tourism study; AC (2001) = Armitage and Conner (2001); BM (2007) = Bamberg and Möser (2007); HS (2017) = Han and Stoel (2017) np = not provided**

Table 9: Updated Meta-Analysis SEM compared with previous studies

Relationship	MASEM	Updated MASEM	BM (2007)	VT study
$ATB \rightarrow INT$	0.320***	0.314***	0.304***	-0.027
$SN \rightarrow INT$	0.181***	0.180***	0.065	0.417***
$PBC \rightarrow INT$	0.208***	0.232***	0.332***	0.342***
$PN \rightarrow INT$	0.312***	0.292***	0.284***	0.124*
$SN \rightarrow ATB$	0.430***	0.430***	0.470***	0.481***
$SN \rightarrow PN$	0.500***	0.500***	0.530***	0.521***

MASEM = our MASEM in the first study; Updated MASEM = MASEM included VT study; VT study = volunteer tourism study
********p***<0.001**
BM (2007) = Bamberg and Möser (2007)

Table 10: Monte Carlo Simulation based on MASEM to determine optimal sample size for future pro-social/environmental research using TPB/NAM

	Minimum number of sample size to achieve the desired power level					
Power level	$ATB \rightarrow INT$	$SN \rightarrow INT$	$PBC \rightarrow INT$	$PN \rightarrow INT$	$SN \rightarrow ATB$	$SN \rightarrow PN$
50	35	**223**	45	41	17	15
60	49	**292**	67	59	25	21
70	64	**366**	91	78	33	28
80	82	**457**	120	102	43	37
90	109	**593**	164	138	59	50

Note: This Monte Carlo simulation simulate 100,000 samples (datasets) from a population with known parameter value, which is generated from the updated MASEM regarding to the desired power level (from 50 to 90). Given that researchers apply the hybrid NAM/TPB model in pro-social/environmental study, our recommended threshold of power analysis is at least 70%, thus meaning that the optimal number to statistically detect the effect size is at least 366 samples.