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Meta-analysis of driving behavior studies and assessment of factors using structural equation modeling

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ABSTRACT

The aim of this paper is to understand the factors that influence unsafe driving practices by examining published studies that utilized the Theory of Planned Behavior (TPB) to predict driving behavior. To this end, it reviews 42 studies published up to the end of 2021 to evaluate the predictive utility of TPB by employing a meta-analysis and structural equation model. The results indicate that these studies sought to predict 20 distinct driving behaviors (e.g., drink-driving, use of cellphone while driving, aggressive driving) using the original TPB constructs and 43 additional variables. The TPB model with the three original constructs is found to account for 32% intentional variance and 34% behavioral variance. Among the 43 variables researchers have examined in TPB studies related to driving behavior, this study identified the six that are commonly used to enhance the TPB model's predictive power. These variables are past behavior, self-identity, descriptive norm, anticipated regret, risk perception, and moral norm. When past behavior is added to the original TPB model, it increases the explained variance in intention to 52%. When all six factors are added to the original TPB model, the best model has only four variables (perceived risk, self-identity, descriptive norm, and moral norm); this model increased the explained variance to 48%. The influence of the TPB constructs on intention is modified by behavior category and traffic category. The findings of this paper validate the application of TPB to predict driving behavior. It is the first study to do this through the use of meta-analysis and structural equation modeling.

1. Introduction

Road traffic crashes are a major public health concern. Globally, there are 1.3 million fatal crashes and 20 to 50 million injury crashes each year (WHO, 2022). Traffic crashes not only cause damage to the vehicles of those involved but may also cause physical injury. The combination of these leads to economic and productivity losses for countries, to be about 3% of their gross domestic products (WHO, 2022). Traffic safety risks are not uniformly distributed across nations and populations.

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They affect pedestrians, cyclists, and motorcyclists more than they do passengers of vehicles, trucks, and buses (Shinar, 2012; Nilsson et al., 2017). Also, low- and middle-income countries are disproportionally affected. Specifically, these countries have about 60% of the world's vehicles, but they have about 90% of the world's road traffic crashes (WHO, 2022). For these reasons, many studies have investigated factors that contribute to crash frequency and injury severity to assist policymakers in identifying the appropriate countermeasures to improve traffic safety.

An abundance of studies has found that human factors or driving behavior are the primary sources of road accidents and fatalities. For instance, Khattak et al. (2003) addressed that dangerous driving behavior, such as reckless driving, speeding, and alcohol/drug use, are the key risk factors in single-truck collisions (rollovers). In Vietnam, more than 95% of road traffic accidents are due to some form of traffic violations, such as using a smartphone while driving, not wearing a helmet when riding a motorcycle, and not following regulatory traffic signs (Truong et al., 2016). Despite the known risks of a crash, drivers often do not intentionally avoid or lessen the extent to which they commit these violations. Such violations are not due to momentary lapses in judgment, but rather, they represent deliberate deviations from driving regulations. Thus, many researchers have attempted to understand the reasons behind this phenomenon to improve traffic safety. This is accomplished by utilizing the Theory of Planned Behavior (TPB) developed by Ajzen in 1991. This theory enables analysts to understand how individuals behave across different settings, scenarios, and situations. Unlocking insight based on attitudes towards behavior enable agencies to understand where barriers exist and how to encourage a change in behavior. It should be noted that while TPB is not the only possible approach to understanding driving behavior, it is by and large the most commonly-used approach compared to social psychological theories and Theory of Reasoned Action (TRA). It has been used successfully to predict and explain a wide range of health behaviors and intentions including driving, smoking, and drinking, among others.

According to Ajzen (1991), human behavior can be predicted and explained in specific contexts through TPB. Intention reflects the belief in an individual's preparedness to perform a given behavior. The intention is influenced by three core constructs, attitude toward the behavior, subjective norm, and perceived behavioral control (PBC). Their inter-relations are depicted in Fig. 1. Attitude is a person's overall positive or negative evaluation of the behavior. Subjective norm is a person's estimate of the social pressure to perform or not to perform the target behavior. PBC describes the individual's perception of the ease or difficulty of performing any given behavior. As a rule, the more intention influences behavior, the more PBC increases, and behavior is more likely to be performed.

There are several motivations for this research paper. First, although a large number of articles have utilized TPB to examine driving behaviors in various contexts since its Introduction in 1991 by Ajzen, they have not yet been synthesized to provide an overview of their applications. Second, existing TPB research in the driving context has yielded conflicting findings across individual studies. For instance, some studies indicated a significant effect of subjective norm on intention to drive risky (e.g., Conner et al., 2003; Wang et al., 2021; Eijigu, 2021), whereas others provided an insignificant effect (e.g., Tang et al., 2021; Tunnicliff et al., 2012). Similarly, Chan (2010) showed that attitude is the strongest predictor of drink-driving intention. However, Moan and Rise (2011) stated that perceived behavioral control has the largest effect on the intention not to drink and drive. Besides, a systematic review uses a qualitative method of subjective nature to collect, arrange, and evaluate research literature. Its outcome comprehensively illustrates what is known in that research area (Card, 2015). A meta-analysis, by contrast, uses a quantitative method based on mathematical and statistical techniques to summarize aggregate information in primary studies. It has more benefits than a systematic review, including (i) achieving accurate statistical estimation about the strength of an association between variables (Paul and Barari, 2022), (ii) determining and

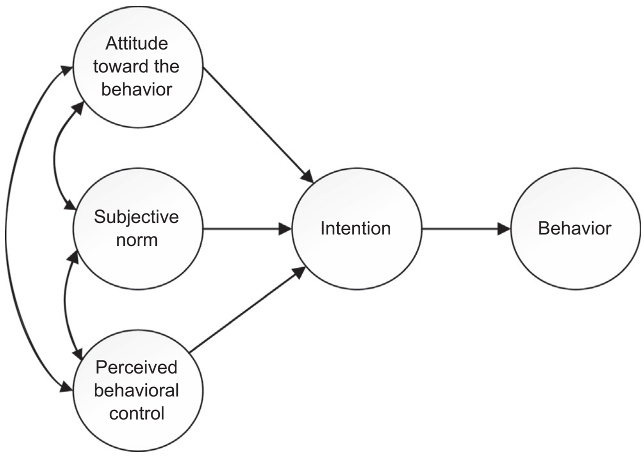


Fig. 1. A diagram representation of TPB (as presented in Ajzen, 1991).

solving conflicting findings across prior studies (Grewal et al., 2018), (iii) extensively increasing sample size due to a pool of sample sizes of individual studies (Cooper, 2015), (iv) examining the role of moderators through assessing size effects in different subsets of participants, (v) creating innovative hypotheses from estimated results for future research (Paul and Barari, 2022). Thus, a meta-analysis is needed to synthesize prior findings to provide an overall effect and elucidate the causal nature of the associations between variables. It is noted that no TPB research has used meta-analysis for driving behaviors up to now despite the spread applications of meta-analysis for medicine and psychology domain. Third, previous TPB studies in the driving domain have primarily focused on the differences between traffic violations and safe driving behaviors, while the differences between traffic violations and unsafe driving practices have not been considered. From the traffic safety literature, driving behaviors are classified as risky or safe. However, in terms of the law, driving behavior is classified as traffic-violating or traffic-conforming. The latter contains both unsafe driving practices (the behavior is unsafe but does not violate traffic regulations, such as yellow-light running) and safe driving practices (e.g., yielding to pedestrians at the crosswalk at intersections). As such, this study seeks to fill a gap in the literature by examining classifying driving behavior into three categories instead of two: traffic-violating, unsafe driving practices, and safe driving practices. Fourth, this study examines the moderating effect of traffic behavior on TPB factors. Finally, a systematic review merely encompasses descriptive analyses. It is unable to validate the causality of the associations, whereas a meta-analysis gauges the unknown effect size between two variables without investigating the influence of other variables. To cope with these systematic review and meta-analysis limitations, MASEM is applied in the present study to test the associations among various constructs and their mediation effects. Moreover, it improves the statistical power of the proposed model (Liang et al., 2021).

In summary, this study aims to integrate systematic review methodology and meta-analysis, and SEM to verify the capacity of TPB for driving behavior analysis and to determine their moderating effects on TPB constructs. It provides new knowledge and findings in driving behavior using TPB to allow researchers to easily identify gaps in the current body of work and expand it in future studies. To this end, the remainder of this paper provides the following information: (i) a brief summary of all prior TPB studies related to driving, (ii) identification of additional prevalent factors in the domain of driving, (iii) evaluation of the predictive validity of TPB components and the contribution of the mentioned additional variables, (iv) determination of innovative moderator variables affecting TPB constructs, and (v) suggestions of interventions based on our findings.

2. Methods

2.1. Literature search

To find relevant TPB studies, we performed a search of published articles, up to the end of 2021, in PsychInfo, ScienceDirect, and Web of Science by employing the terms *factors*, *drive*, *intention*, *risk behaviors*, *traffic violations, TPB, etc.* as keywords. The papers returned by the citation databases were screened to retain only those that dealt with quantitative TPB research in the driving domain. This process resulted in an initial 63 applicable papers that underwent further screening, as explained below.

2.2. Sample criteria

A study was used for the meta-analysis if it satisfied two requirements as follows,

(1) The study reported Pearson correlation coefficients between all constructs in the TPB model;
(2) The study reported sample size and measures of all constructs in the TPB model (e.g., standard deviation, response scale, response anchor, and scale correspondence).

The process of literature collection consisted of three steps. In step 1, the search with the mentioned keywords resulted in 942 articles. In step 2, these articles were screened to exclude articles not related to driving behavior, which reduced the sample to 63 papers. In step 3, after applying research sample criteria to the 63 papers, the sample is further reduced to 42 papers applicable for a meta-analysis. There are 40 articles and two conference proceedings having 56 individual tests with a combined sample size of 28,723 observations. Among the 42 studies in the final sample, 29 examined rule-breaking-driving behaviors, 9 studied unsafe driving practices, and 4 investigated safe driving practices. Regarding geographic coverage, 3 used data from North America, 15 were conducted in Europe, 17 used data from Asia, 5 studies from the Australian continent, and 2 extracted data from Africa. This sample encompassed 13 constructs in accordance with 72 relationships, 56 tests investigating driving intention and only 25 out of the 56 tests reporting the actual behavior, 45 tests studied driving behavior regarding motor vehicles, and 11 tests analyzed driving behavior in line with two-wheeled motor. Additional information about these studies is provided in Table A1.

2.3. Data analysis

Of particular interest is the connection between study characteristics and effect size. In the present study, the meta-analytic random effects procedures proposed by Hedges (1983) were applied to estimate weighted mean correlations. This was accomplished using a meta-analytic SPSS program written by Field and Gillett (2010). The meta-analysis on correlations included effect size, heterogeneity, and publication bias.

2.4. Structural equation modeling analysis

Structural equation model (SEM), a multivariate technique, has prevalently been used in social and behavioral science fields to fit and test hypothesized models. A meta-analysis is a statistical approach to synthesize the data from independent primary studies with the same questions based on identical variables. MASEM is established on a combination of meta-analysis and SEM. It not only facilitates the assessment of path models but also verifies the models incorporating additional variables that were not investigated in independent individual studies. As a result, significant predictors, establishing interactions between factors, and proportions of explained variance of the model are transparently estimated. A number of researchers have concentrated on applications of MASEM in different domains, such as psychology, information systems, management, and sociology (Steinmetz and Block, 2022). More importantly, in TPB review research up to date, their MASEM applications are increasingly taken in numerous areas, including physical activity (Hagger et al., 2002), smoking behavior (Topa and Moriano, 2010), organic food consumption (Scalco et al., 2017), knowledge sharing (Tuyet-Mai et al., 2018), health behavior (Hagger et al., 2022), social commerce (Leong et al., 2022). Based on our knowledge, however, the MASEM model has not yet been applied in the transportation area. According to Cheung and Cheung (2016), MASEM is commonly conducted in two steps. Firstly, the covariance (or correlation) matrices are included together to set the pooled correlation matrix. Secondly, this matrix is utilized to fit structural equation models. The MASEM procedure implemented in the IBM SPSS Amos 22 program is used to test the predictive utility of TPB factors and extended variables.

3. Results

3.1. Description of studies

A total of 20 driving behaviors were examined in the sample of 42 studies. These behaviors include driving too fast for the condition, using of cellphone while driving, driving under the influence, driving through a red light, reckless driving with

Table 1
Summary of select TPB studies involving driving behaviors.

First author (year)	Behavior	Behavior category	Country	Traffic category	Sample size	Additional factors	R^2-TPB		R^2-model	
							Intention	Behavior	Intention	Behavior
Conner (2003)	Speeding violation	Traffic violation	UK	Primarily cars	162	Moral norm*, anticipated regret*, past behavior	n/a		45	
Eijigu (2021)	Use of cellphone while driving	Traffic violation	Ethiopia	Mixed	155	Risk perception	45		49	
Chan (2010)	Driving under the influence	Traffic violation	China	Primarily cars	124	Invulnerability	n/a		79	
Wang (2021)	Continuous lane changing	Unsafe driving practice	China	Primarily cars	481	Moral norm*, perceived risk	n/a		48	
Guggenheim (2020)	Reckless driving with friends	Unsafe driving practice	Israel	Primarily cars	166	Peer pressure, social costs, communication, shared commitment	21		32	
Poulter (2008)	Comply with traffic regulations	Safe driving practice	England	Primarily cars	226	n/a	n/a	28		
Yang (2019)	Drivers' yielding behavior at a crosswalk	Safe driving practice	China	Primarily cars	332	Risk perceptions, new countermeasures, traditional countermeasures	n/a		n/a	

* Factor is not significant; R^2-TPB: total explained variance by the traditional TPB variables; R^2-model: total explained variance by the TPB variables and other factors in the model; n/a: not applicable.

friends, and other traffic violations. Some of the studies examined good driving behaviors. Table 1 provides details of seven studies with different driving behaviors. Details of all 42 studies can be found in Table A1 in the Appendix. Column 1 of Table 1 lists the first author's last name and the year the study was published. Column 2 shows the driving behavior the study examined. This study classifies the driving behavior as either a traffic violation, an unsafe driving practice, or a safe driving practice. This information is presented in Column 3. Column 4 shows the country where data were collected for the study. Column 5 specifies the traffic flow characteristic, either primarily passenger cars or mixed traffic. A mixed traffic stream consists of trucks, cars, mopeds, and bicycles. Column 6 shows the study's sample size. Column 7 lists the variables considered in the study in addition to the three TPB variables (i.e., attitude, subjective norm, and PBC). Columns 8 and 9 show the proportion of the variance for the intention and behavior interpreted by the three original TPB constructs. Columns 10 and 11 show the ratio of the intentional and behavioral variance described by the three original TPB constructs and additional ones.

3.2. Strength of relationships of TPB variables and driving behavior and additional variables with intention

A total of 43 additional factors were examined in the sample of 42 studies. Regarding O'Keefe (2002), if an additional variable was found to be a significant indicator and was investigated in three other studies, this variable was deemed to have considerable potential to improve explained variance in driving behavior. There were six such variables: descriptive norm, moral norm, self-identity, risk perception, anticipated regret, and past behavior. These factors are frequently utilized in conjunction with three TPB variables with the aim of increasing the model's explained variance. These variables were combined with attitude, subjective norm, PBC, intention, and behavior to provide an 11×11 weighted correlation matrix for the SEM analyses, as shown in Table 2. The harmonic mean (5942) was used as the sample size of this correlation matrix.

First, a meta-analysis of estimated results from the 42 studies was performed. Table 2 shows that all pairs pass the correlation analysis test except for four pairs (i.e., past behavior-risk perception, past behavior-self-identity, anticipated regret-descriptive norm, self-identity-behavior). All weighted averages of sample correlations (r_+) are significant at $p < 0.001$, and none of the 95% confidence intervals (*CI*) contain a zero. All fail-safe numbers (*FSN)* far exceed the limited value of $5k + 10$, where k is the number of independent tests, so these correlations are robust (Rosenthal, 1984). According to Hunter et al. (1982), applying the Chi-squared statistic, χ^2, is to conduct a homogeneity analysis with the purpose of testing variation among estimated correlations. If χ^2 is nonsignificant, estimated effects across primary studies are homogeneous. In contrast, it is essential to search for moderating variables to explain latent reasons for the heterogeneity of effect size estimations between studies if χ^2 is significant. Table 2 indicates that the larger number of the χ^2 is significant. Thus, these correlations can be used in the next step to assess the strength of associations of TPB variables with driving behavior and the association of six additional variables with intention.

Pairs of subjective norm-intention, attitude-intention, PBC-intention, intention-behavior, and PBC-behavior were investigated to determine the strength of TPB constructs using the obtained correlations. The three key TPB constructs affect intention; thus, the correlation of variables to intention is a critical factor in establishing the explained power of TPB. To examine the association of six additional factors to driving intention, correlations of past behavior-intention, risk perception-intention, moral norm-intention, self-identity-intention, descriptive norm-intention, and anticipated regret-intention were evaluated. A total of 11 pairs, as shown in the first 11 rows of Table 2, were analyzed. Cohen (1992) provided guidance for interpreting the sample weighted average correlations (r_+). The effect size is small if r_+ changes between 0.1 and 0.3, moderate if r_+ varies from 0.3 to 0.5, and large if r_+ is greater than 0.5. As shown in Table 2, the average correlations of attitude-intention, moral norm-intention past behavior-intention, anticipated regret-intention, and intention-behavior are large (their $r_+ \geq 0.5$). Only the association of self-identity-intention indicates a small effect size (its $r_+ < 0.1$). All other associations indicate moderate effect size, with r_+ values being between 0.2 and 0.3.

Overall, the results showed that attitude is the most vital determinant of intention among the three TPB variables, and intention contributes more than PBC to driving behavior. Six additional factors (i.e., past behavior, perceived risk, moral norm, self-identity, anticipated regret, and descriptive norm) were proven to be significant predictors in the TPB models used to examine driving behavior. The correlations obtained for attitude-intention, subjective norm-intention, moral norm-intention, and anticipated regret-intention are almost identical to the results reported by the following studies: (1) Armitage and Conner (2001) indicated the correlation of attitude and subjective norm to intention to be 0.49 and 0.34, respectively; (2) Conner and Armitage (1998) found the correlation between intention and moral norm to be 0.50, and (3) Sandberg and Conner (2008) found the anticipated regret-intention correlation to be 0.47. Moreover, the correlations obtained in this study for PBC-intention, intention-behavior, and PBC-behavior are similar to those reported by Armitage and Conner (2001) with $r_+ = 0.43$, $r_+ = 0.47$ and $r_+ = 0.37$, respectively. Similarly, Rivis and Sheeran (2003) provided the correlation between descriptive norm and intention to be 0.46, which is comparable to this study's finding. However, the correlations obtained in this study for past behavior-intention and self-identity-intention are different from those reported by Conner and Armitage (1998) ($r_+ = 0.69$ versus $r_+ = 0.51$; $r_+ = 0.08$ versus $r_+ = 0.27$). Previous research did not consider perceived risk as a significant predictor. However, the moderate effect size of perceived risk found in this study indicates that this factor should be considered in future studies.

Table 2
Results of correlation analysis.

Association	k	Total N	Weighted r_+	LI	UI	χ^2	FSN
ATT-INT	*56*	*28723*	*0.513*	*0.432*	*0.586*	*54.95**	*138356*
SN-INT	*56*	*28723*	*0.304*	*0.200*	*0.401*	*44.68**	*27573*
PBC-INT	*51*	*28085*	*0.340*	*0.253*	*0.423*	*66.47***	*54017*
PB-INT	*23*	*16666*	*0.690*	*0.631*	*0.742*	*23.14**	*79746*
RE-INT	*8*	*6559*	*−0.515*	*−0.607*	*−0.410*	*22.13***	*5682*
DN-INT	*9*	*8914*	*0.330*	*0.186*	*0.460*	*14.05*	*2177*
MN-INT	*17*	*11575*	*−0.481*	*−0.576*	*−0.373*	*13.63**	*14349*
RP-INT	*10*	*5661*	*−0.177*	*−0.270*	*−0.146*	*12.52**	*764*
SI-INT	*8*	*8642*	*−0.085*	*−0.121*	*−0.069*	*17.81**	*388*
INT-BEH	*25*	*12316*	*0.584*	*0.533*	*0.632*	*30.48**	*44286*
PBC-BEH	*20*	*10916*	*0.242*	*0.084*	*0.389*	*19.53**	*3899*
ATT-SN	55	27342	0.327	0.227	0.420	49.73***	33723
ATT-PBC	51	27323	0.279	0.189	0.363	68.09*	35154
ATT-PB	23	16666	0.469	0.413	0.522	30.30*	28213
ATT-RE	8	6559	−0.472	−0.555	−0.381	23.49**	5110
ATT-DN	9	8914	0.250	0.158	0.338	14.31*	1415
ATT-MN	17	11575	−0.365	−0.498	−0.216	23.69*	9686
ATT-RP	10	5661	−0.152	−0.204	−0.100	11.12	640
ATT-SI	8	8642	0.092	0.080	0.104	21.46**	220
ATT-BEH	26	12748	0.416	0.304	0.517	19.49*	17729
SN-PBC	50	25942	0.163	0.075	0.248	54.48*	7007
SN-PB	12	9925	0.098	0.008	0.188	10.55*	1711
SN-RE	7	6388	0.254	0.086	0.407	20.78**	2171
SN-DN	4	4511	0.360	0.244	0.465	4.95*	746
SN-MN	9	9169	0.004	0.002	0.007	7.52	175
SN-RP	6	4543	0.149	0.105	0.193	5.03*	148
SN-SI	7	8482	0.256	0.117	0.386	18.09*	455
SN-BEH	24	11884	0.216	0.075	0.349	15.39***	3005
PBC-PB	18	15266	0.324	0.180	0.453	21.03**	10571
PBC-RE	8	6559	−0.245	−0.302	−0.188	6.25*	1016
PBC-DN	9	8914	0.184	0.002	0.355	11.96	531
PBC-MN	17	11575	−0.013	−0.004	−0.022	23.05**	1990
PBC-RP	10	5661	−0.156	−0.291	−0.015	14.33*	687
PBC-SI	8	8642	−0.023	−0.030	−0.017	8.56*	189
PB-RE	7	6388	−0.470	−0.563	−0.364	12.81*	3913
PB-DN	4	7081	0.350	0.279	0.417	2.88	1244
PB-MN	10	9026	−0.398	−0.468	−0.323	12.45*	4964
PB-RP	3	2850	0.143 ns	−0.308	0.542	1.44	30
PB-SI	4	7024	−0.055 ns	−0.176	0.007	3.29	31
PB-BEH	11	7074	0.607	0.531	0.673	9.89**	11409
RE-DN	1	1403	−0.39 ns	−0.39	−0.39	[-]	[-]
RE-MN	8	6559	0.563	0.473	0.642	24.47*	6961
RE-SI	4	5840	0.056	0.018	0.094	2.84	25
RE-BEH	2	1574	−0.459	−0.591	−0.304	1.45	259
DN-MN	4	4742	−0.123	−0.188	−0.056	2.69*	117
DN-RP	2	2460	0.018	0.005	0.031	2.28	44
DN-SI	3	3863	0.044	0.018	0.070	1.38	38
DN-BEH	3	4135	0.348	0.290	0.403	1.76	529
MN-RP	3	2941	0.318	0.147	0.471	2.36*	275
MN-SI	6	8300	0.060	0.022	0.092	4.67*	503
MN-BEH	8	5070	−0.398	−0.463	−0.328	4.38	1924
RP-SI	3	2692	0.297	0.262	0.331	1.12*	193
RP-BEH	2	2771	−0.459	−0.488	−0.429	4.1	695
SI-BEH	2	3703	−0.033 ns	−0.339	0.279	1.08	75

Note: $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$; ns: Nonsignificant; k: Number of independent tests; N: Sample size; LI: Lower limit; UI: Upper limit; ATT: Attitude; SN: Subjective norm; PB: Past behavior; RE: Anticipated regret; DN: Descriptive norm; MN: Moral norm; RP: Risk perception; SI: Self-identity; INT: Intention; BEH: Behavior; The italic numbers indicate the pairs explicated.

3.3. Influence of moderating variables in the associations between TPB components

As alluded to in the previous section, to explain potential causes of the heterogeneity of effect sizes across studies, a moderator analysis was conducted to test the role of moderating variables on the relationships between the TPB factors (i.e., attitude-intention, PBC-intention, subjective norm-intention, PBC-behavior, intention-behavior). The two moderator variables examined are the behavior category and traffic category. As explained previously and shown in Table 1, there are three

Table 3
Results of moderator analysis.

Relationship	Moderator	k	N	r_+	95% CI	χ^2	Z
ATT-INT	(1) Violation	39	17072	0.563	0.48–0.64	39.3*	Z_{12} = 17.77***
	(2) Unsafe	13	9616	0.389	0.16–0.58	13.2*	Z_{23} = 0.77
	(3) Safe	4	2035	0.373	0.15–0.56	2.50*	Z_{13} = 10.45***
	(4) Primarily cars	51	26098	0.546	0.48–0.60	62.07*	Z_{45} = 24.76***
	(5) Mixed	5	2625	0.105	0.07–0.20	4.04*	
SN-INT	(1) Violation	39	17072	0.399	0.31–0.48	28.3*	Z_{12} = 51.57***
	(2) Unsafe	13	9616	0.275	0.18–0.37	13.15*	Z_{23} = 27.82***
	(3) Safe	4	2035	0.417	0.17–0.60	2.08*	Z_{13} = 0.92
	(4) Primarily cars	51	26098	0.303	0.19–0.40	41.79*	Z_{45} = 1.08
	(5) Mixed	5	2625	0.323	0.24–0.40	6.49*	
PBC-INT	(1) Violation	33	15318	0.338	0.21–0.45	37.66**	Z_{12} = 2.66**
	(2) Unsafe	14	10732	0.308	0.20–0.41	19.65**	Z_{23} = 7.93***
	(3) Safe	4	2035	0.470	0.25–0.60	2.42**	Z_{13} = 6.7***
	(4) Primarily cars	47	25814	0.361	0.27–0.44	55.70**	Z_{45} = 8.0***
	(5) Mixed	4	2271	0.200	0.16–0.23	7.16**	
INT-BEH	(1) Violation	18	8768	0.576	0.51–0.63	22.40*	Z_{12} = 2.60**
	(2) Unsafe	5	2724	0.613	0.47–0.70	3.91*	Z_{23} = 1.25
	(3) Safe	2	824	0.581	0.35–0.72	1.85*	Z_{13} = 0.21
	(4) Primarily cars	21	9846	0.613	0.57–0.65	27.13*	Z_{45} = 11.76***
	(5) Mixed	4	2470	0.421	0.19–0.60	3.56*	
PBC-BEH	(1) Violation	13	7368	0.172	0.16–0.20	12.10*	Z_{12} = 6.4***
	(2) Unsafe	5	2724	0.307	0.15–0.45	4.31*	Z_{23} = 5.56***
	(3) Safe	2	824	0.492	0.10–0.75	2.11*	Z_{13} = 9.92***
	(4) Primarily cars	16	8446	0.269	0.12–0.45	14.52*	Z_{45} = 6.34***
	(5) Mixed	4	2470	0.130	0.08–0.18	3.38*	

Note: *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$; k: Number of independent tests; N: Sample size; *CI*: Credibility interval; Z: Fisher's Z test; Z_{12}: compared correlations between traffic violations and unsafe driving practices; Z_{23}: compared correlations between unsafe and safe driving practices; Z_{13}: compared correlations between traffic violations and safe driving practices; Z_{45}: compared correlations between primarily cars and mixed traffic.

behavior categories: traffic violation, unsafe driving practices, and safe driving practices. These three categories were coded as 1, 2, and 3, respectively. There are two traffic categories: mixed and primarily cars. These two categories were coded as 4 and 5, respectively. The Fisher's Z test was used to compare two correlation coefficients from independent samples and test the significant difference between effect sizes. Table 3 illustrates the calculated results from the moderator analysis.

All three behavior types were found to moderate all associations between the TPB constructs. For traffic violations and unsafe driving practices, attitude substantially affects the TPB predictors-intention relationships, whereas PBC influences safety performance. The moderator analysis results confirmed that attitude is the best indicator of intention on risky driving behaviors, and PBC is the best predictor of intention on safe driving. The average correlations of three pairs of the TPB variables with the intention for the traffic violation category are stronger than those of unsafe driving practices, except for two pairs of association: intention-behavior and PBC-behavior. These results indicate that TPB constructs are better predictors of traffic violations than unsafe driving practices.

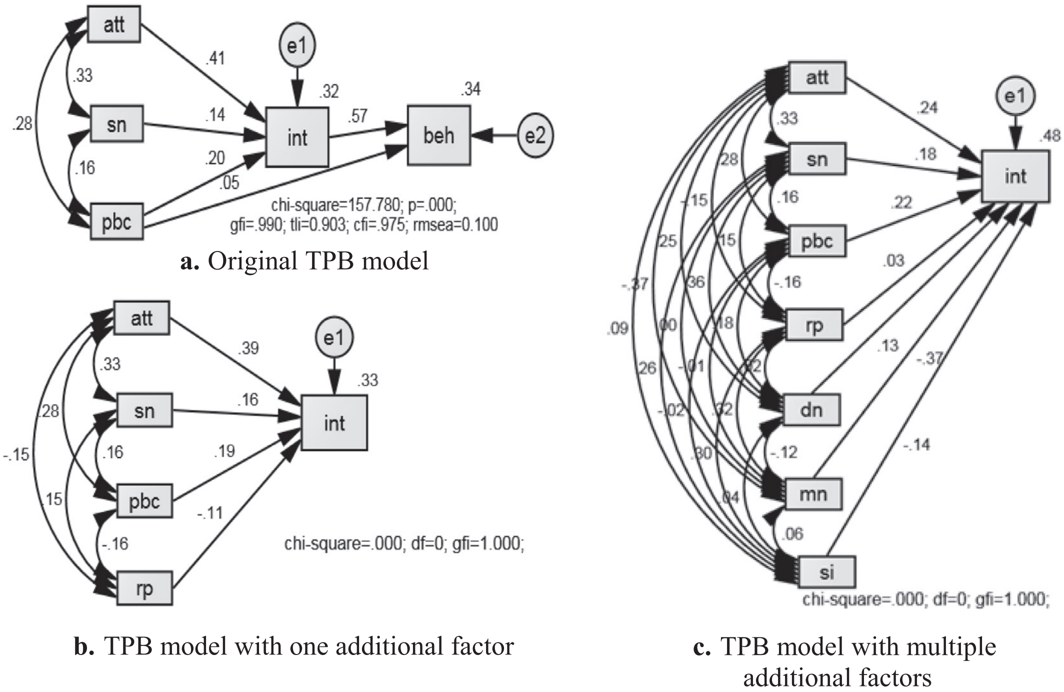
There is a significant difference in effect sizes between primarily cars and mixed traffic categories for all pairs of relationships, with the primarily cars traffic category having higher significance. These results recommend that three TPB constructs are better indicators of the primarily cars traffic category than mixed. A possible explanation for this is that the characteristics of studies that dealt with mixed traffic are very different compared to those that dealt with primarily car traffic. This finding indicates that driving behaviors in primarily car traffic have higher variance, possibly due to lower psychological stress than in mixed traffic.

3.4. Predictive utility of TPB factors and other variables

3.4.1. Strength of TPB factors

A model with only the original TPB constructs is employed to test the strength of TPB factors. The Chi-Square test and several fit indices can assess how well a hypothesized model fits the data. The four model fit indices that are widely applied and used in the present study are the root mean square error of approximation (*RMSEA*), goodness-of-fit (*GFI*), comparative fit index (*CFI*), and Tucker and Lewis Index (*TLI*). *RMSEA* is a parsimony-adjusted index to determine the difference between hypothesized and perfect models. *GFI* is an alternative to Chi-square statistics and is defined as the proportion of variance through computing population covariance. Conversely, *CFI* and *TLI* are incremental fit indices that compare the fit of a hypothesized model to that of a baseline model (Xia and Yang, 2019). According to Byrne (2001), a good fit is indicated by the proportion of χ^2 to the degree of freedom without exceeding 3 ($\chi^2/df < 3$), $RMSEA \leq 0.08$, $GFI \geq 0.90$, $CFI \geq 0.90$, and $TLI \geq 0.90$.

The model with only the original TPB constructs has the following results: χ^2 (2) = 157.78, p < 0.01; *GFI* = 0.990; *CFI* = 0.975; *TLI* = 0.903; *RMSEA* = 0.10. Three of the five indices indicate a good fit, except for χ^2/df and *RMSEA*. It should be noted that χ^2 is very sensitive to the sample size *(N)*, and studies have indicated that it is not a practical fitness index.



a. Original TPB model

b. TPB model with one additional factor

c. TPB model with multiple additional factors

Fig. 2. Estimated results of structural equation models.

Table 4
Results of the estimated parameters of the proposed models to predict intention.

Models with one additional variable						
Variables	*RP* β	*DN* β	*MN* β	*SI* β	*PB* β	*RE* β
ATT	0.39	0.39	0.24	0.42	0.25	0.34
SN	0.16	0.09	0.19	0.18	0.14	0.12
PBC	0.19	0.19	0.24	0.19	0.16	0.27
Added factor	−0.11	0.17	−0.39	−0.16	0.57	−0.54
R^2	33	35	45	35	52	37
R^2 change	1	3	13	3	20	5
Models with multiple additional variables						
Variables	Phase 1 β	Phase 2 β	Phase 3 β	Phase 4 β	Phase 5 β	
ATT	0.41	0.39	0.37	0.23	0.24	
SN	0.14	0.16	0.11	0.15	0.18	
PBC	0.20	0.19	0.17	0.22	0.22	
RP		−0.11	−0.11	−0.02	0.03	
DN			0.17	0.13	0.13	
MN				−0.37	−0.37	
SI					−0.14	
R^2	32	33	36	46	48	
R^2 change		1	3	10	2	

β: Standard regression weights (all coefficients are significant at the 0.001 level); Phase: The combination of extended factors; R^2: Model's total explained variance; R^2 change: Model's increase in variance.

If the sample size is more than 200, then the *p*-value of that study is most likely to be significant (Newsom, 2012). In this study, $N = 5942$, so $\chi^2/df = 78.89$ and $p < 0.01$. Also, Kenny et al. (2014) recommended that *RMSEA* should not be considered for models with small degrees of freedom, which is 2 in our case. For these reasons, the fit of the hypothesized model is accepted. This model indicates that attitude and PBC are dominant predictors of driving intention, and the three TPB antecedents account for 32% of the variance in intention. Intention and PBC explain 34% of the variance in behavior (Fig. 2a). Elliott (2012) reviewed 15 correlational studies that addressed driving violations, and he reported that TPB factors accounted for more than 25% of the variance in both intention and behavior. Similarly, Armitage and Conner (2001) reported that TPB factors in social behavior studies account for 27% intentional variance and 29% behavioral variance. The findings from this study corroborate those reported in the literature.

3.4.2. Strength of TPB factors and one additional variable to predict intention

An extended model with the original TPB constructs and one additional variable was used to predict intention. This model is shown in Fig. 2b and has perceived risk as the additional variable. It can be seen in Fig. 2b that this model is saturated, and its estimates are statistically significant. Adding perceived risk to the model contributes to a 1% increase in explained variance for intention (33% vs. 32% for the model shown in Fig. 2a). Thus, evidence suggests that this model yields a good fit. The same analysis was performed for five other additional variables: self-identity, description norm, moral norm, anticipated regret, and past behavior. Adding each of these variables to the model with the three original TPB constructs enhanced the explained variance in intention by 3%, 13%, 3%, 20%, and 5%, respectively. The results in Table 4 indicate that past behavior is the strongest predictor among those examined in this study to predict driving intention. Sandberg and Conner (2008), Rivis and Sheeran (2003), and Conner and Armitage (1998) reported that self-identity, descriptive norm, and anticipated regret increased explained variance in intention by 1%, 5%, and 7%, respectively. These values are similar to the ones found in this study, 1% vs. 3% for self-identify, 5% vs. 3% for descriptive norm, and 7% vs. 5% for anticipated regret. Conner and Armitage (1998) indicated that moral norms increased explained variance in intention by 4% and past behavior by 7.2%. These values are much lower than those found in this study, 4% vs. 13% for moral norms and 7.2% vs. 20% for past behavior.

3.4.3. Strength of TPB factors and multiple additional factors to predict intention

An extended model with the original TPB constructs and an additional six variables (self-identity, perceived risk, norm of description, norm of morality, past behavior, and anticipated regret) previously analyzed are used to predict intention. Different combinations of these variables were tested to obtain the best model (one that gives the highest rate of explained variance and fit). The results of this model are shown in Fig. 2c. Among the six variables evaluated, only four were found to be significant: risk perception, norm of description, norm of morality, and self-identity. These variables increased the explained variance in intention by 1%, 3%, 10%, and 2%, respectively. The results are summarized in Table 4. It can be seen in Fig. 2c that the model with multiple additional variables is saturated and provides adequate goodness of fit. Adding the mentioned four variables to the model results in an increase of 16% in explained variance for intention (48% vs. 32% for the model shown in Fig. 2a).

4. Discussion

The meta-analysis performed in this study using data reported from 42 papers aimed to understand (1) the strength of associations between TPB components and driving behavior, (2) the role of moderator variables affecting relationships between TPB factors, and (3) the predictive utility of TPB factors and other variables. This study provides a pioneering approach to analyzing TPB research in driving behavior by combining meta-analysis and SEM. To date, 20 unique driving behaviors have been examined using TPB. These behaviors can be broadly classified as traffic violations, unsafe and safe driving practices. To predict these behaviors, a total of 43 factors have been investigated in conjunction with the original three TPB constructs. Among these additional factors, six have been found to be significant and frequently used in TPB studies dealing with driving behavior. These factors are past behavior, risk perception, moral norm, self-identity, descriptive norm, and anticipated regret.

The meta-analysis confirmed the efficacy of TPB in predicting driving behavior. The weighted average correlation of the relationship between attitude and intention is the strongest among the three pairs of TPB variables, followed by PBC-intention. The strength of the intention-behavior correlation in driving behaviors ($r_+ = 0.58$) is larger than the one reported by Armitage and Conner (2001) ($r_+ = 0.47$). Attitude is found to be the best predictor of intention among the three TPB variables, and intention contributes more than PBC to driving behavior. The model shown in Fig. 2a indicates that attitude ($\beta = 0.41$), PBC ($\beta = 0.20$), and subjective norm ($\beta = 0.14$) are good predictors of intention. The proportion of the variance explained by this model in intention and behavior is 32% and 34%, respectively. These values are higher than those reported in TPB studies for other behaviors. For example, Topa and Moriano (2010) reported that TPB models explained 12% of the variance in intention and 13% of the variance in behavior for smoking. This finding corresponds to the intuition that driving behaviors is complex and can vary considerably due to not only the characteristics and circumstances of the drivers but also that of the roadway and other nearby drivers/users. Both behavior category and traffic category were found to influence all TPB variables' relationships. Most importantly, attitude is the best determinant of risky driving intentions, whereas PBC is the best indicator of safe driving intentions. The predictive power of TPB variables in traffic violations and primarily cars traffic category is better than that of unsafe driving practices and mixed traffic category, respectively. Overall, meta-analysis substantiates the necessity of its employment for transportation research via this study. It obtains effect sizes with precise validity to elicit conclusions of associations between TPB variables and commonly used-additional variables. It also plays a crucial role in investigating the moderation of the behavior and traffic categories by evaluating estimated effects between subgroups of observations. Furthermore, it contributes to creating accurate input data for setting the pooled correlation matrix used for an SEM analysis.

The predictive power of TPB models for driving behaviors can be increased by including one additional variable. Among the six variables examined, past behavior was found to be the most significant, and it increased the explained variance in intention by 20%. This finding is consistent with the 20% reported by Cestac et al. (2011) in their study to identify factors that affect the intention to drive faster than the posted speed limit. However, it is much higher than the 7.2% reported by Conner and Armitage (1998) and 11% reported by Elliott et al. (2003). In the context of traffic violations, this particular factor needs to be examined further to fully understand its effect on intention. Regarding actions that caused negative consequences, Sandberg and Conner (2008) reported that the anticipated regret-intention association has a significant effect size ($r_+ = 0.47$), and anticipated regret increased explained variance in intention by 7%. This study obtained similar values, likely due to the fact the majority of the 42 studies in the sample investigated traffic violations as opposed to unsafe or safe driving practices. The descriptive norm was found to have a moderate effect size, and it increased the explained variance in intention by 3%. This finding is consistent with those reported by Rivis and Sheeran (2003). The moral norm was found to increase the explained variance in intention by 13%, three times higher than the value reported by Conner and Armitage (1998). This is likely due to traffic violations being evaluated negatively compared to safe driving practices. Conner and Armitage (1998) reported that self-identity is a significant predictor of intention. This study found that it has a small effect size; however, it increased the explained variance in intention by 3%. Thus, it is suggested that self-identity is a significant indicator of driving intention. To date, only a few TPB studies have investigated the role of perceived risk in driving intention, and no study has conducted a meta-analysis based on the TPB to assess perceived risk as an additional variable to predict driving intention. The application of MASEM in this study is to understand its effect. The results indicated that it had a small to medium effect size and contributed an extra 1% of the variance in intention. Thus, it is also a significant predictor of drivers' intention to either violate traffic regulations, engage in unsafe driving practices, or engage in safe driving practices. Collectively, including self-identity, perceived risk, descriptive norm, and moral norm in the TPB model will have greater explanatory power. Overall, based on many of our findings corroborating previous TPB analyses, efficient MASEM application in the field of transportation is warranted. MASEM is a better statistical method than traditional meta-analysis since it estimates effect sizes investigated on the influence of other constructs in the model. Also, its results are easily assessed through the goodness-of-fit of the proposed model. Further, it pools a large number of correlation matrices obtained from a meta-analysis in as to establish the pooled covariance matrix that is significantly greater than the sample size under ordinary SEM. Finally, MASEM can effectively test models involving additional variables that were not included in each primary study.

There are several practical takeaways from this study's findings. To improve roadway traffic safety, interventions elicited from TPB variables are necessary. That is, it is necessary to address drivers' intentions. The factors affecting drivers' intention to either violate traffic regulations, drive in an unsafe manner, or drive in a safe manner, in order of importance, are attitude, PBC, and subjective norm. Thus, if the budget does not allow for the development and implementation of interventions to address all three factors, changing drivers' attitudes should be the first priority, followed by PBC and subjective norms. Educational programs and traffic safety campaigns are tools that have been considered to have positive effects on drivers' attitudes. For example, Tang et al. (2021) proposed the use of educational, training, and reward programs to change electric bike riders' attitudes toward traffic violations. Specifically, they used videos to show how electric bike riders' behavior caused accidents to evoke unfavorable emotions toward such behaviors. Countermeasures such as the presence of law enforcement have been shown to be effective in changing PBC; Forward (2006) reported that drivers with higher PBC are more likely to engage in safe driving practices. Educational awareness programs are needed to educate the public toward standard driving norms. Parents play a crucial role in shaping their children's driving behavior. Harith and Mahmud (2020) suggested that rather than just telling their children to drive safely, parents should comply with road traffic laws to be a good example. Given that the strength of associations of TPB constructs is modified by traffic flow category, transportation agencies should be aware that what works for one country will not necessarily work for another with a different traffic flow category. That is, programs and countermeasures targeting drivers in the U.S. with primarily cars in the traffic stream may not be effective in Vietnam, where the traffic is mixed. Similarly, a separate set of programs and countermeasures need to be developed for different groups of drivers with different intentions: violating traffic regulations, engaging in unsafe driving practices, or engaging in safe driving practices. Past behavior is a good predictor of a driver's intention. Thus, programs should be developed to target those with repeated offenses. Anticipated regret, self-identity, and perceived risk were found to affect intention. To influence drivers to drive more cautiously, transportation agencies could implement countermeasures that improve situational awareness and deter drivers from committing other violations (e.g., high traffic fines). Lastly, moral and descriptive norms need to be cultivated through education, family settings, and public events.

This research has several limitations that need to be considered when interpreting its outcomes. Using the pooled correlation matrix as input to the structural equation model assumes that the correlation matrix is homogeneous. However, effect sizes were found to be heterogonous. Due to this shortcoming, the goodness-of-fit of the original TPB model (in Fig. 2a) showed only marginal fit. Therefore, future research should be performed using a large number of primary studies and utilize the parameter-based meta-analytic structural equation modelling approach. Such an approach would allow for the investigation of heterogeneity of the parameters across studies. This study did not make a distinction between traffic accident risk (e.g., head-on collision, rear-end collision, and collision with pedestrians) and general traffic risk (e.g., as driver or occupant of a motor vehicle, as a bicyclist, and as a pedestrian). Nordfjærn and Rundmo (2009) stated that these two risk types are different. Thus, future research efforts should seek to address the different types of risks. In addition, this study did not consider factors related to traffic conditions and the consequences of driving behaviors. According to Sukor et al. (2016), factors related to traffic conditions are known to influence driving behavior. Thus, future studies should consider incorporating these moderating variables into the path diagram of the TPB model.

5. Conclusions

The current research is an initial effort to perform a systematic review of 42 TPB studies related to driving behavior. It demonstrates the efficacy of TPB models via meta-analytic structural equation modeling analyses. Among the 43 factors researchers have examined in TPB studies related to driving behavior, this study identified six that are commonly used to increase the TPB model's predictive power. The TPB model with the three original constructs is capable of explaining 32% of the variance in intention, 52% with past behavior added to the original TPB model, and 48% with perceived risk, self-identity, descriptive norm, and moral norm added to the original TPB model. The conclusions on the contribution of TPB constructs and these additional variables provide theoretical support for TPB in the context of driving. Lastly, the current paper recommends that the influence of the TPB constructs on intention is modified by behavior category and traffic category.

Declaration of Competing Interest

Nathan Huynh is an editorial board member/editor-in-chief for International Journal of Transportation Science and Technology and was not involved in the editorial review or the decision to publish this article. All authors declare that there are no competing interests.

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Appendix A

See Table A1.

Table A1
Summary of all TPB studies involving driving behaviors.

No	First author (year)	Behavior	Behavior category	Country	Traffic category	Sample size	Additional factors	R^2 -TPB		R^2 - model	
								Intention	*Behavior*	*Intention*	*Behavior*
1	Cestac (2011)	Speeding violation	Traffic violation	France	Primarily cars	3002	DN, SS*, self-descriptions, typical-deviant descriptions*, similarity typical deviant, judgement of speeding risk, number of times ticketed*, PB	28		72	
2	Castanier(2013)	Speeding violation	Traffic violation	France	Primarily cars	280	Perceived autonomy*, perceived capacity, PB	68	42	80	51
		Drink-driving	Traffic violation	France	Primarily cars	280	Perceived autonomy*, perceived capacity*, PB	56	33	79	41
		Following closely	Traffic violation	France	Primarily cars	280	Perceived autonomy*, perceived capacity*, PB	54	21	69	30
		Mobile phone use while driving	Traffic violation	France	Primarily cars	280	Perceived autonomy*, perceived capacity*, PB	73	58	85	67
		Disobeying road signs	Traffic violation	France	Primarily cars	280	Perceived autonomy, perceived capacity, PB*	57	38	76	42
3	Parker (1992) [a]	Speeding violation	Traffic violation	England	Primarily cars	881		47			
4	Wanner (2008)[a]	Speeding violation	Traffic violation	Sweden	Primarily cars	162		70			
		Speeding violation	Traffic violation	Sweden	Primarily cars	156		31			
5	Chen (2011)	Speeding by motorcyclists	Unsafe driving practice	Taiwan	Primarily cars	277	Perceived enjoyment, concentration	none	none	none	none
6	Chorlton (2012)	Speeding by motorcyclists	Unsafe driving practice	UK	Primarily cars	1381	PB, AR*, moral norm, self-identity, perceived susceptibility	38		60	
		Go for it [b]	Unsafe driving practice	UK	Primarily cars	1116	PB, AR, moral norm*, self-identity, perceived susceptibility*	42		62	
		Group riding	Unsafe driving practice	UK	Primarily cars	1940	PB, AR, moral norm, self-identity, perceived susceptibility*	45		57	
7	Conner (2003)	Speeding violation	Traffic violation	UK	Primarily cars	162	Moral norm*, AR*, PB	none		45	
8	Conner (2007)	Speeding is assessed by the simulator	Traffic violation	UK	Primarily cars	83	PB*, AR*, moral norm	53	21	83	42
		Speeding is assessed by speed camera	Traffic violation	UK	Primarily cars	303	PB*, AR*, moral norm	46	12	77	21
9	Elliott (2003)	Compliance with speed limits	Safe driving practice	UK	Primarily cars	598	PB	48	32	76	54
10	Elliott (2010)	Speeding violation	Traffic violation	UK	Primarily cars	1403	Affective attitude, self-efficacy, perceived controllability*, self-identity*, moral norm, AR, DN*, PB	55	47	68	51
11	Forward (2009)	Speeding violation	Traffic violation	Sweden	Primarily cars	275	Perceived ease, perceived control, DN*, PB, PR*	47		71	
		Overtaking	Traffic violation	Sweden	Primarily cars	275	Perceived ease, perceived control, DN, PB, PR*	33		60	
12	Dinh (2013)	Speeding violation	Traffic violation	Japan	Primarily cars	367	DN*, PB, self-judged driving skill, accepted belief of speeding behavior, perceived function of residential streets, perceived right of street users, perceived appropriateness of speed limit	41	22	65	48
13	Atombo (2016)	Speeding violation	Traffic violation	Ghana	Mixed	354	Driver Behavior Questionnaire	47		64	
		Overtaking	Traffic violation	Ghana	Mixed	354	Driver Behavior Questionnaire	38		43	

Table A1 (*continued*)

No	First author (year)	Behavior	Behavior category	Country	Traffic category	Sample size	Additional factors	R^2 -TPB		R^2 - model	
								Intention	*Behavior*	*Intention*	*Behavior*
14	Javid (2019) [a]	Speeding	Unsafe driving practice	Oman	Mixed	303	Speeding passion, speeding culture	none	none	31	35
15	Boissin (2019)	Men's speeding behavior	Unsafe driving practice	Oman	Mixed	1107		18	24		
		Students' speeding behavior	Unsafe driving practice	Oman	Mixed	655		21	39		
16	Paris (2008) [a]	Speeding violation	Traffic violation	France	Primarily cars	116	Negative attitude, positive attitude, explicit norm, implicit norm, perceived internal control, perceived external control	none	33		
		Compliance with speed limits	Safe driving practice	France	Primarily cars	116	Negative attitude, positive attitude, explicit norm, implicit norm, perceived internal control, perceived external control	36	58		
17	Elliott (2007)	Speeding violation	Traffic violation	UK	Primarily cars	123		54	67		
18	Elliott (2010) [a]	Speeding on urban roads by motorcyclists	Traffic violation	Scotland	Primarily cars	110	Self-identity*, perceived group norm*, group identification*	42		43	
		Speeding on carriageways by motorcyclists	Traffic violation	Scotland	Primarily cars	110	Self-identity, perceived group norm, group identification	44		62	
19	Leandro (2012)[a]	Lower speed selection	Safe driving practice	Costa Rica	Mixed	210		13	68		
20	Lheureux (2016)[a]	Speeding violation	Traffic violation	France	Primarily cars	642	Habit	60	64	68	67
		Drink-driving	Traffic violation	France	Primarily cars	642	Habit	43	56	49	59
21	Forward (2020) [a]	Speeding by motorcyclists	Unsafe driving practice	Sweden	Primarily cars	945	DN, prototype evaluation, prototype similarity	45		49	
22	Tavafian (2011) [a]	Compliance with speed limits	Safe driving practice	Iran	Mixed	246		25	41		
23	Jiang (2021)	Speeding at intersections	Unsafe driving practice	China	Primarily cars	980	PR	none		34	
24	Walsh (2008)	Using a phone while driving	Traffic violation	Australia	Primarily cars	796	PR*	32		49	
25	Nemme (2010)	Sending texts while driving	Traffic violation	Australia	Primarily cars	169	Group norm, moral norm, PB	28	14	51	39
		Reading texts while driving	Traffic violation	Australia	Primarily cars	169	Group norm, moral norm, PB	29	10	50	49
26	Zhou (2009) [a]	Use a handheld phone while driving	Traffic violation	China	Primarily cars	164		44			
		Use a hands-free phone while driving	Traffic violation	China	Primarily cars	164		42			
27	Zhou (2012) [a]	Handheld phone answer while driving	Traffic violation	China	Primarily cars	333	PB	54		64	
		Hands-free phone answer while driving	Traffic violation	China	Primarily cars	333	PB	61		67	
28	Gauld (2014)	Concealed texting while driving	Traffic violation	Australia	Primarily cars	171	AR*, moral norm, mobile phone involvement	69		75	
		Obvious texting while driving	Traffic violation	Australia	Primarily cars	171	AR*, moral norm, mobile phone involvement*	55		64	

(*continued on next page*)

Table A1 (*continued*)

No	First author (year)	Behavior	Behavior category	Country	Traffic category	Sample size	Additional factors	R^2 -TPB		R^2 - model	
								Intention	*Behavior*	*Intention*	*Behavior*
29	Eijigu (2021)	Use of smartphone while driving	Traffic violation	Ethiopia	Mixed	155	PR	45		49	
30	Waddell (2014)	Answer a call, read texts while driving	Traffic violation	Australia	Primarily cars	181	DN	47		56	
		Make a call, send texts while driving	Traffic violation	Australia	Primarily cars	181	DN	47		59	
31	McBride (2020)	Texting while driving	Traffic violation	USA	Primarily cars	524	Perceived disadvantage, perceived advantage	none		71	
32	Qu (2020)	WeChat-sending texts while driving-	Traffic violation	China	Primarily cars	286	Group norm, moral norm*	none	none	none	39
		Reading texts while driving-	Traffic violation	China	Primarily cars	286	Group norm, moral norm*	none	none	none	42
		Sending pictures while driving-	Traffic violation	China	Primarily cars	286	Group norm, moral norm*	none	none	none	50
		Browsing pictures while driving-	Traffic violation	China	Primarily cars	286	Group norm, moral norm*	none	none	none	47
		Sending voice messages while driving-	Traffic violation	China	Primarily cars	286	Group norm, moral norm*	none	none	none	42
		Listening to voice messages while driving-	Traffic violation	China	Primarily cars	286	Group norm, moral norm*	none	none	none	49
33	Przepiorka (2018)	Texting while driving	Traffic violation	Poland	Primarily cars	298		41			
34	Jiang (2019)	Using a phone while cycling	Traffic violation	China	Primarily cars	603	Mobile phone addiction, distraction perception	none		none	
35	Nguyen (2020) [a]	Using a phone while riding	Traffic violation	Vietnam	Mixed	291	Phoning-riding habit, health motivation	none	none	31	47
36	Rozario (2010)	Hand-held phone use while driving	Traffic violation	Australia	Primarily cars	160	Neuroticism*, extroversion*	37		39	
37	Marcil (2001) [a]	Drink-driving	Traffic violation	France	Primarily cars	113		64			
38	Moan (2011)	Not drink-driving	Safe driving practice	Norway	Primarily cars cars	879	DN, moral norm	10		12	
39	Andrew (2018)	Motorcyclists' cannabis driving behavior	Traffic violation	USA	Primarily cars	311	PB	25		58	
40	Chan (2010)	Drink-driving	Traffic violation	China	Primarily cars	124	Invulnerability	none		79	
41	Potard (2018)	Drink-driving	Traffic violation	France	Primarily cars	368	PB, danger invulnerability, interpersonal invulnerability, psychological invulnerability	44		52	
42	Gonzalez-Iglesias (2015) [a]	Drink-driving	Traffic violation	Spain	Primarily cars	274	Self-efficacy to avoid, perceived driving self-efficacy*, optimism bias*, alcohol use	32		50	
43	Yao (2011)	Ebikers' red-light running behavior	Traffic violation	China	Primarily cars	232	Perceived risk*, utility perception, self-identity	14		33	
44	Palat (2012) [a]	Yellow light running	Unsafe driving practice	France	Primarily cars	103	Perceived risk*, AR*, direct experience of risk*, PB*, facilitating circumstances	43		73	
45	Satiennam (2018) [a]	Motorcyclists' red-light running behavior	Traffic violation	Thailand	Mixed	246		45	31		
		Motorcyclists' red-light running behavior	Traffic violation	Thailand	Mixed	246	Positive outcome, negative outcome, injunctive norm, DN, facilitating circumstance, impeding circumstance	12	49		

Table A1 (*continued*)

No	First author (year)	Behavior	Behavior category	Country	Traffic category	Sample size	Additional factors	R^2 -TPB		R^2 - model	
								Intention	*Behavior*	*Intention*	*Behavior*
46	Anh (2018) [a]	Speeding without helmet use of motorcyclists	Traffic violation	Vietnam	Mixed	268	Perceived enjoyment, concentration	none	none	none	none
47	Tang (2020)	Ebikers' red-light running behavior	Traffic violation	China	Primarily cars	1035	PB	none	none	80	74
		Ebikers' red-light running behavior	Traffic violation	China	Primarily cars	1035	PB, prototype perceptions, willingness	none	none	82	81
48	Yang (2018)	Ebikers' red-light running behavior	Traffic violation	China	Primarily cars	160	PR, DN*, moral norm, conformity tendency*, self-identity*	16		42	
49	Shen (2020)	Ebikers' red-light running behavior	Traffic violation	China	Primarily cars	228	Conformity tendency, traffic environment	76		87	
50	Susilo (2015) [a]	Motorcyclists' violations	Traffic violation	Indonesia	Mixed	983		none	none	none	none
51	Cheng (2021)	Ebikers' violations	Traffic violation	China	Primarily cars	432		56	29		
52	Tang (2021)	Ebikers' violations	Traffic violation	China	Primarily cars	2326	Moral norm*, DN, PR*, PB, legal norm*, conformity tendency, self-identity*	51	43	69	50
53	Parker (1995) [a]	Cut across traffic	Traffic violation	England	Primarily cars	598	Moral norm, AR	35		48	
		Weaving	Traffic violation	England	Primarily cars	598	Moral norm, AR	37		52	
		Overtake	Traffic violation	England	Primarily cars	598	Moral norm, AR	34		53	
54	Wang (2019) [a]	Lane change violation	Traffic violation	China	Primarily cars	506		none	none	none	none
55	Wang (2021)	Continuous lane change	Unsafe driving practice	China	Primarily cars	481	Moral norm*, perceived risk	none		48	
56	Yao (2019) [a]	Navigation use while driving	Unsafe driving practice	China	Primarily cars	415	Navigation information quality, navigation involvement, distract perception	42	none	61	none
57	Jiang (2017)	Fatigued driving	Unsafe driving practice	China	Primarily cars	214		24	none	39	45
58	Li (2021)	Risky driving	Unsafe driving practice	China	Primarily cars	471	PR, sensation seeking	none	none	80	64
59	Guggenheim (2020)	Reckless driving with friends	Unsafe driving practice	Israel	Primarily cars	166	Peer pressure, social costs, communication, shared commitment	21		32	
60	Li (2016)	Competitive driving	Unsafe driving practice	China	Primarily cars	225	Social environment	none	42	none	42
61	Poulter (2008)	Comply with traffic regulations	Safe driving practice	England	Primarily cars	226		none	28		
62	Yang (2019)	Yielding behavior	Safe driving practice	China	Primarily cars	332	PR, new countermeasure, traditional countermeasure	none		none	
63	Tunnicliff (2012) [a]	Motorcyclists' unimpaired riding behavior	Safe driving practice	Australia	Primarily cars	179	Specific subjective norm, group norm*, self-identity*, sensation seeking*, aggression*	11		39	
		Motorcyclists' stunt behavior	Unsafe driving practice	Australia	Primarily cars	183	Specific subjective norm*, group norm*, self-identity, sensation seeking, aggression*	53		66	

Note: [a] The study is not included in the meta-analysis; [b] The motorcyclists open up the throttle and accelerate the motorcycle up to high speed; * The factor is insignificant; R^2-TPB: Total explained variance of the traditional TPB variables; R^2-model: Total explained variance of the TPB components and other factors in the model; DN: Descriptive norm; SS: Sensation seeking; PB: Past behavior; AR: Anticipated regret.

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