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Modeling farmers' behavior in the use of agricultural pesticides: Application of an extended theory of planned behavior

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Abstract

Background: Farmers often use agricultural pesticides (Ps) unsafely, posing significant occupational hazards. This study aimed to identify factors associated with behavior in Ps use among farmers using an extended version of the theory of planned behavior (TPB).

Methods: This study investigated 326 farmers of Khuzestan using the TPB and an extended version, ETPB-P, which included perceived threat and exaggerated risk-related messages as additional variables to the original theory.

Results: All TPB variables, except for subjective norms ($\beta = 0.072$, $t = 1.303$), were significantly associated with behavioral intention (BI) to take protective measures in pesticide use ($P < 0.05$). TPB paths could predict 32% ($R^2 = 0.32$) of agricultural pesticide use behaviors, while the ETPB-P paths improved predictive ability to 60% ($R^2 = 0.60$). The ETPB-P model demonstrated stronger power in predicting farmers' intention and behavior to use pesticides safely than the original TPB.

Conclusion: The extended TBP model can serve as a useful framework for designing occupational health promotion programs that could improve safety behavior in pesticide use among farmers.

Keywords: Farmers, Pesticide, Occupational health, Theory of planned behavior, Least-squares analysis

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Introduction

Indiscriminate use of pesticides (Ps) is a growing concern in many developing countries where these substances are often believed to be effective against destructive pests (1). However, less than 1% of the Ps applied in the field finally reach the intended target pests, with the rest entering the soil, water, and air, leading to environmental pollution and concerns about side effects on non-target organisms (2). Therefore, Ps residues are now recognized as a major environmental and human health threat (3). Pesticides exposure can have both acute effects (e.g., mild or severe poisoning) and long-term effects on humans, including neurological diseases, respiratory diseases, genetic disorders, and adverse reproductive effects (4). Farmers and farm workers who regularly handle these chemicals are the most vulnerable to Ps exposure (5), while Ps residues in drinking water or food pose a threat to the health of the general population (6). Misuse of Ps is responsible for 180 000 deaths among farmers and farm workers annually, with about three million people experiencing serious poisoning and 25 million experiencing mild poisoning each year (7).

To reduce potential risks associated with Ps use, it is crucial to understand the factors that govern the likelihood of risk, including the characteristics of the population being exposed (8). Some experts propose that the first step in reducing the risks of Ps use is to examine the behavior of those using pesticides (9). For example, proper disposal of Ps waste is one of the fundamental concerns when it comes to Ps use. In addition to empty containers, toxic substances may remain on containers even after use (10). The residue of the spray solution after use, the washing places of sprayers, and the washing solutions of sprayers are among the main sources of Ps waste that require attention (11). Negligent disposal of such waste can be hazardous to farmers if proper protective measures are disregarded (12). Moreover, it can pose a threat to non-target organisms, such as beneficial insects and aquatic organisms (13). Farmers often use pesticides carelessly, especially in developing countries, and do not properly dispose of the waste generated (7). A previous study conducted in Iran found that 85% of the farmers stored chemical pesticides at their place of residence (14).

Farmers may lack awareness regarding the proper disposal of residual waste (15). The behavior of farmers concerning Ps use indicates that many farmers are unaware of the potential dangers of these chemicals, which normally occur due to unsafe practices (16). Such practices can pose significant risks to the farmers, hindering their ability to protect themselves (17). Factors that influence farmers' behavior in this area are numerous and often unclear. Previous research has shown that attitudes towards occupational health and safety measures, awareness of such measures, and self-efficacy are directly linked to farmers' adoption of healthy practices, collectively accounting for 73% of the variance in farmers' safety behavior (18).

Human behavior is influenced by beliefs and attitudes, so without changing beliefs and adopting appropriate behaviors, reducing the risk factors associated with Ps use in society cannot be guaranteed (19). Therefore, it is crucial to investigate farmers' Ps use behaviors, given that it is the primary aspect of handling these hazardous substances (20). Limited research has been conducted on farmers' safety behaviors related to Ps use (7). The present study focused on safety behavior among farmers in using Ps, including proper disposal of spray solution residues, use of designated sprayer washing areas, safe disposal of detergents, and use of personal protective equipment. Although several studies used the theory of planned behavior (TPB) (16), there has been little research on this topic in Iran, with only a handful of studies applying the well-known TPB (2). The TPB is a robust framework for understanding both intention and behavior, and it has proven effective in explaining various behaviors across different contexts (20).

Theoretical framework and hypothesis development

The theory of planned behavior

The TPB (Figure 1) has received considerable attention in health behavior literature (21). It aims to explain behaviors that individuals can control, suggesting that their attitudes, subjective norms, and perceived behavioral control (PBC) shape their intention and engagement in a particular behavior (22). Attitudes refer to the evaluation of the positive or negative outcomes of a behavior, subjective norms include normative beliefs and the appropriate motivation to perform a behavior that peers and important people perceive as right, and PBC represents the degree to which an individual feels that behavior is under their voluntary control (2). Although previous studies have shown the TPB's effectiveness in predicting behavior, particularly in predicting farmers' intentions to utilize personal protective equipment, it is crucial to extend the theory with additional variables to address its limitations (23). This is because the TPB lacks comprehensiveness, failing to account for other influential factors like moral norms and disregarding indirect effects (20). The TPB allows for the inclusion of additional predictive variables to enhance its predictive power, with potential variables such as normative factors, self-identity, anticipated affect, and past behavior identified to improve its efficacy. However, it is essential for new variables in the TPB to be conceptually independent, applicable to a wide range of behaviors, and possess causal relationships in determining intention or action (24).

To enhance the predictive ability of the TPB, this study proposes an extension of the original model by incorporating perceived threat and perceived exaggeration of health-related messages from the Extended Parallel Process Model (25) (Figure 2). Perceived threat, encompassing perceived severity and perceived susceptibility, represents an individual's belief regarding the potential harm or danger posed by a situation. Perceived exaggeration of health-related messages involves the belief that health messages overstate the existence of features that do not exist, exaggeratedly presenting information beyond reality (26).

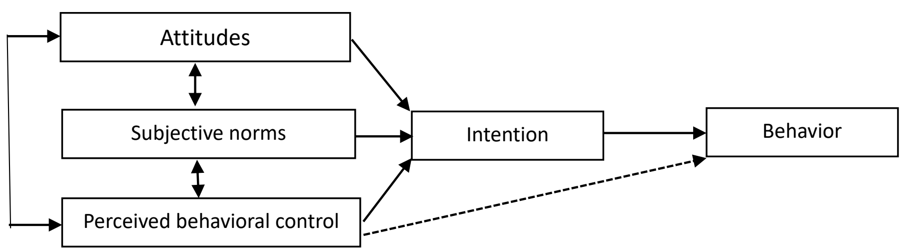

Figure 1. The theory of planned behavior (22)

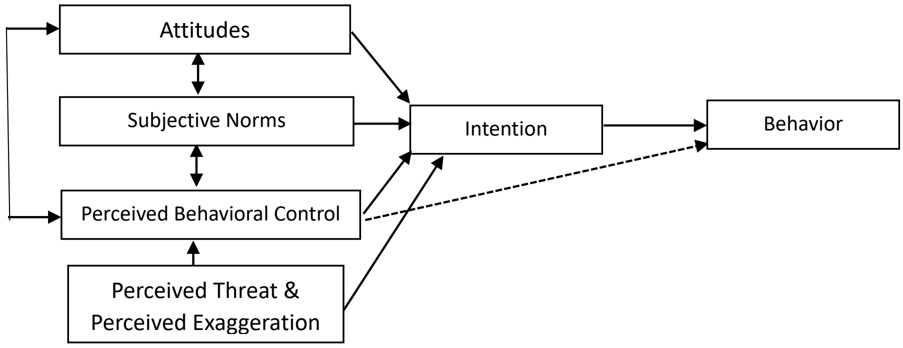

Figure 2. The proposed extended theory of planned behavior

By incorporating these variables, motivation can be integrated into the extended TPB, an important construct known to improve the model's predictive capacity (26). Additionally, perceived threat can complement PBC, which is already included in the TPB (24), as individuals weigh their perceived threat against their perceived ability to cope to determine their motivation to form an intention (25,26).

Perceived exaggeration of health-related messages, as a measure of reactance within the Extended Parallel Process Model (25,26), was included in the proposed extended version of the TPB framework for this study to address individuals' potential negative motivational responses to health-related messages, particularly those related to situations such as pesticide use. The addition of perceived exaggeration of health-related messages has the potential to provide insight into the resistance to the adoption of health behaviors in response to health-related messages.

Several recent studies have applied the TPB to explore factors influencing pro-environmental behavioral intentions (BIs), such as water conservation (27), green purchasing (28), and climate change action (29). This current study extends the application of the TPB to examine health behavior among farmers, contributing significantly to the understanding of TPB's applicability in Ps use. Incorporation of perceived threat addresses the acknowledged but contentious influence of risk perception on safety behavior (30).

Previous studies have highlighted the benefits of integrating or expanding existing models to improve their efficacy in practical applications (31). Research suggests that adding additional variables to the TPB can increase the explanatory power of the model in explaining safety behavior (32). Understanding safety behavior has implications for the development of effective interventions and policies aimed at promoting safe behaviors across diverse settings.

Objective

This study aimed to determine predictors of safety behavior among vegetable farmers in Ahvaz, Iran, using an extended version of the TPB.

Materials and Methods

Participants and sampling

This study aimed to determine factors related to Ps use behavior in the farming community of Khuzestan in southwest Iran, from March to June 2022. The sample size was determined considering 50% prevalence, 6% precision, a two-sided significance level, and 90% power, with an estimated dropout rate of 10%. In total, 330 questionnaires were distributed. The inclusion criteria were the ability to read and write in Persian (the official Iranian language), informed consent to participate in the study, and at least one year of farming experience. The exclusion criterion was failure to complete the questionnaire. Participants were selected by first preparing a list of all farmers. Then, farmers were randomly included in the study based on their identification number using simple random sampling. Recruitment and data collection involved various methods, including email, phone calls, and face-to-face interactions. Fewer than 10% of farmers, primarily those with higher education levels, requested an online questionnaire link. These processes involved researchers introducing themselves and explaining the research objectives before inviting farmers to participate in the research. After explaining the study's objective and obtaining informed consent, a research assistant distributed and collected the research questionnaires from participants.

Measurement and data collection

Data were collected using a questionnaire that was developed in alignment with Ajzen's guidelines (24), aiming to measure behavior in Ps use of and related factors. The item pool of the questionnaire draft consisted of 79 items, including demographic variables (8 items). After omitting duplicate items, they were divided into 7 dimensions, 5 of which (45 items) measured variables related to TPB, i.e., attitudes towards Ps use (7 items), subjective norms in Ps use (4 items), PBC of Ps use (4 items, e.g., I can buy and use pesticides as recommended), intention to take protective measures in Ps use (e.g., to use personal protective equipment during pesticide spraying) (5 items), and behavior in Ps use (7 items, e.g., I buy and spray pesticides as recommended on the label or by professionals). The other two dimensions of the questionnaire were created to measure two additional variables: perceived threat (4 items) and perceived exaggeration of health-related messages (2 items). All items were rated on a five-point Likert-type scale. Refer to the supplementary 1 for a breakdown of items and examples from the questionnaire for each model. Face validity, as assessed by impact score and content validity indices (including content validity index and ratio), yielded scores of 0.83 and 0.67, 0.89, respectively. The intraclass correlation coefficient for indirect items was 0.89, and Cronbach's alpha range for the questionnaire dimensions was 0.73-0.91.

Data analysis

Statistical description of demographic details of the respondents

Data were entered into Microsoft Excel (Microsoft Corporation 2018) for conducting statistical analysis of data using the Statistical Package for Social Sciences (SPSS 26) (33). Demographic information of the respondents was analyzed, and comparisons of mean intention and Ps use behavior among farmers were conducted based on demographic variables, employing ANOVA and independent t-tests.

Hypothesis testing

Hypotheses were categorized based on Ajzen's TPB (13), examining relationships between TPB variables and their connection to BI, as well as testing BI and PBC. Additionally, the relationship between new variables (perceived threat and perceived exaggeration of health-related messages) and Ajzen's TPB variables (13) was tested. Finally, the predictive power of both statistical models derived from the hypotheses was compared to determine their effectiveness in predicting farmers' Ps use behavior.

Data analysis approach

Data were analyzed using inferential statistics and structural equation modeling (SEM) to examine hypotheses and identify predictive factors related to farmers Ps use behavior. The least-squares procedure was used to substitute for SEM (34), and partial least squares SEM (PLS-SEM) was performed using SmartPLS 3 software (35). PLS-SEM applied the variance-based method to concurrently test relationships between the baseline model's constructs (36) and highlighted predictions in the statistical model from this study (37).

PLS-SEM was selected for its suitability in the context with recommended sample sizes, distributional assumptions, and statistical power (37). This method, widely used in medical science studies, offers advantages in testing conceptual frameworks (38). Given that it does not rely on assumptions such as the normal distribution of observed variables and large sample size (39), PLS-SEM is particularly well-suited for this study.

The analytical approach encompassed reliability analysis, convergent and discriminant validity, questionnaire, and model reliability. Employing the component-dependent method, the software facilitated the measurement of validity, reliability, and relations among variables. Two systematic methodologies were employed, following Hair et al (37) and Herjanto and Amin's (40) recommendations for: 1) the measurement model and 2) the structural model. Data quality was ensured by considering several metrics, including Cronbach's alpha (0.6), composite reliability (CR) (0.7), rho_A (0.7), average variance extracted (AVE) (0.5), and loading factor (0.7) (49-51). Bootstrap and t-statistic processes were used to ascertain significant path coefficients above 1.96 at the 95% confidence interval (41).

Measurement model

Assessment of the measurement model involved calculation of internal consistency reliability, convergent validity, and discriminant validity, in line with recommendations by Amin et al (42) and Hair et al (37).

Reliability

Both Cronbach's alpha and CR were utilized to evaluate the internal consistency reliability of the measurement model. While Cronbach's alpha values above 0.7 are generally considered reliable, sensitivity to the number of items in the scale (36) and population differences is acknowledged. Therefore, CR was also considered, as suggested by Hair et al (36).

Convergent validity

Convergent validity was assessed through standardized factor loading, CR, and AVE computations for each construct (43).

Discriminant validity

The Fornell-Larcker procedure was employed to establish discriminant validity, which states that the square root of the AVE for each latent variable should be greater than the correlations between that variable and other latent variables (44).

Structural model

Following external model testing, the endogenous model, illustrating the relationship between latent variables, underwent testing using a 5000 resampling technique. Research hypotheses were evaluated at this step, with the path coefficient (β) and the t-statistic being calculated according to the recommendations by Hair et al (37). The β values were used to determine the strength of the relationship between each pair of variables. Analysis included examination of PLS estimation results for the structural model, R^2 values for endogenous variables, path coefficients, and item loadings for the research constructs.

Overall model fit assessment

Goodness of fit (GoF) was assessed using two metrics: the standardized root mean squared residual (SRMR) and the GoF index. SRMR value, which aims to prevent model misspecification (45), is typically considered satisfactory when it falls below 0.10 or 0.08 (46). Additionally, the GoF index (with $0 < GoF < 1$), proposed for PLS path modeling (47), is calculated as the geometric mean of the average communality and average R^2 for endogenous constructs. Given that in the PLS path modeling approach, communality equals AVE, a cutoff value of 0.5 for communality was used, as recommended by Fornell and Larcker (48). Furthermore, based on the effect sizes for R^2 proposed by Cohen (49) (small: 0.02; medium: 0.13; large: 0.26), we derived the following GoF criteria for small, medium, and large effect sizes of R^2 by substituting the minimum average AVE of 0.50 and effect sizes for R^2 as per previous document (50).

Values of $GoF_{small} = 0.1$, $GoF_{medium} = 0.25$, and $GoF_{large} = 0.36$ are recommended to represent weak, moderate, and strong values, respectively, for the overall model fit. In this study, the complete model yielded a GoF value of 0.471, which shows a strong overall model fit (50).

Results

Demographics

In this study, 330 farmers were invited to participate, but four incomplete or corrupted questionnaires were excluded, leaving a final sample of 326 participants. The sample was diverse in terms of gender, educational background, economic situation, and age. Farmers with higher education levels had higher mean scores of intentions to engage in safety behavior than farmers with lower education levels ($P = 0.000$), except for farmers with diplomas (Table 1). There was no significant difference in intention between age groups ($P = 0.177$), whereas the mean score of safety behavior was significantly lower among farmers aged 30-40 years than that of the farmers above 50 years old ($P = 0.01$). Farmer expertise was not associated with differences in the mean score of safety behavior ($P = 0.510$). Additionally, female farmers had significantly higher mean scores for safety behaviors than male farmers ($P = 0.047$) (Table 1).

Hypothesis testing with the TPB-P (Model 1)

Two structural equation models were developed to forecast behavior in Ps use among vegetable and summer labor farmers. The first model (Figure 3) was created to test the hypotheses and illustrate factor loading of each variable of the TPB-P as a baseline framework. This was done to identify factors associated with the safety behavior of farmers concerning Ps use.

In the measurement model, latent variables (ovals) were linked to their corresponding indicators (rectangles). In the structural model, the results of the test of the hypotheses of the first group of research are shown

Table 1. Demographic characteristics of the study participants

Demographic variable	Group	Number of respondents (%)	Intention Mean (SD)	*P* value	Behavior Mean (SD)	*P* value
Education level	Diploma	247 (74.8)	23425	0.000 [a]	2.2805 (0.68)	0.000 [a]
	Associates degree	40 (12.1)	23200		2.3000 (0.76)	
	Bachelor	33 (10.0)	18424		1.8009 (0.88)	
	Master	6 (1.8)	15333		1.5000 (0.47)	
Age (year)	< 30	109 (33.3)	2.2556 (0.73)	0.177 [a]	2.2632 (0.75)	0.001 [a]
	30-40	99 (30.3)	2.1758 (0.73)		2.0043 (0.69)	
	41-50	65 (19.9)	2.3169 (0.72)		2.2769 (0.72)	
	> 50	54 (16.5)	2.4407 (0.70)		2.4603 (0.67)	
Expertise (Year)	≤5	116 (35.2)	2.2052 (0.71)	0.510 [a]	2.2180 (0.76)	0.234 [a]
	6-10	72 (21.8)	2.3667 (0.79)		2.1210 (0.71)	
	11-20	73 (22.1)	2.2603 (0.73)		2.2446 (0.77)	
	21-30	40 (12.1)	2.3900 (0.69)		2.2071 (0.51)	
	> 31	22 (6.7)	2.2273 (0.79)		2.5390 (0.84)	
Income	Excellent	21 (6.4)	2.2952 (0.67)	0.958 [a]	2.2177 (0.61)	0.863 [a]
	Good	150 (45.5)	2.2733 (0.72)		2.2267 (0.74)	
	Medium	134 (40.6)	2.2597 (0.77)		2.1940 (0.73)	
	Weak	21 (6.4)	2.3524 (0.60)		2.3401 (0.84)	
Gender	Male	256 (77.6)	2.2336 (0.73)	0.054 [b]	2.1780 (0.74)	0.047 [b]
	Female	70 (21.2)	2.4229 (0.70)		2.3735 (0.66)	

[a] Compares means by ANOVA; [b] Compares means by t-test.

in the first model (Figure 3), which confirmed all hypotheses, except one (subjective norms and BI). The hypothesis based on the relationship between subjective norms and BI was rejected. According to these results, subjective norms have an indirect relationship through attitude and PBC with intention. The other TPB paths between variables in the first statistical model were able to predict 32% of farmers' safety behavior in the use of agricultural pesticides ($R^2=0.323$) (Figure 3). The results of the methods related to the measurement model and the structural model are presented in Table 2.

Hypothesis testing with the ETPB-P (Model 2)

The second statistical model (Figure 4) aimed to test additional hypotheses (Table 3) and illustrate factor loading of each variable of ETPB-P as an extended framework. The model in Figure 2 is a proposed model for creating initial assumptions based on Ajzen's model (1991). The model in Figure 4 is presented as a confirmed model based on the results of the hypothesis tests. As shown in Figure 4, the inclusion of two new variables in the original TPB led to changes in the structure of previous variables, and some items were categorized under different variables. The Categories of hypotheses based on Ajzen's TPB are shown in Table 2 [The results of testing the first hypotheses in TPB-P (Model 1)]. Preliminary PBC (i.e., initial perception or belief an individual holds regarding their ability to perform a specific behavior),

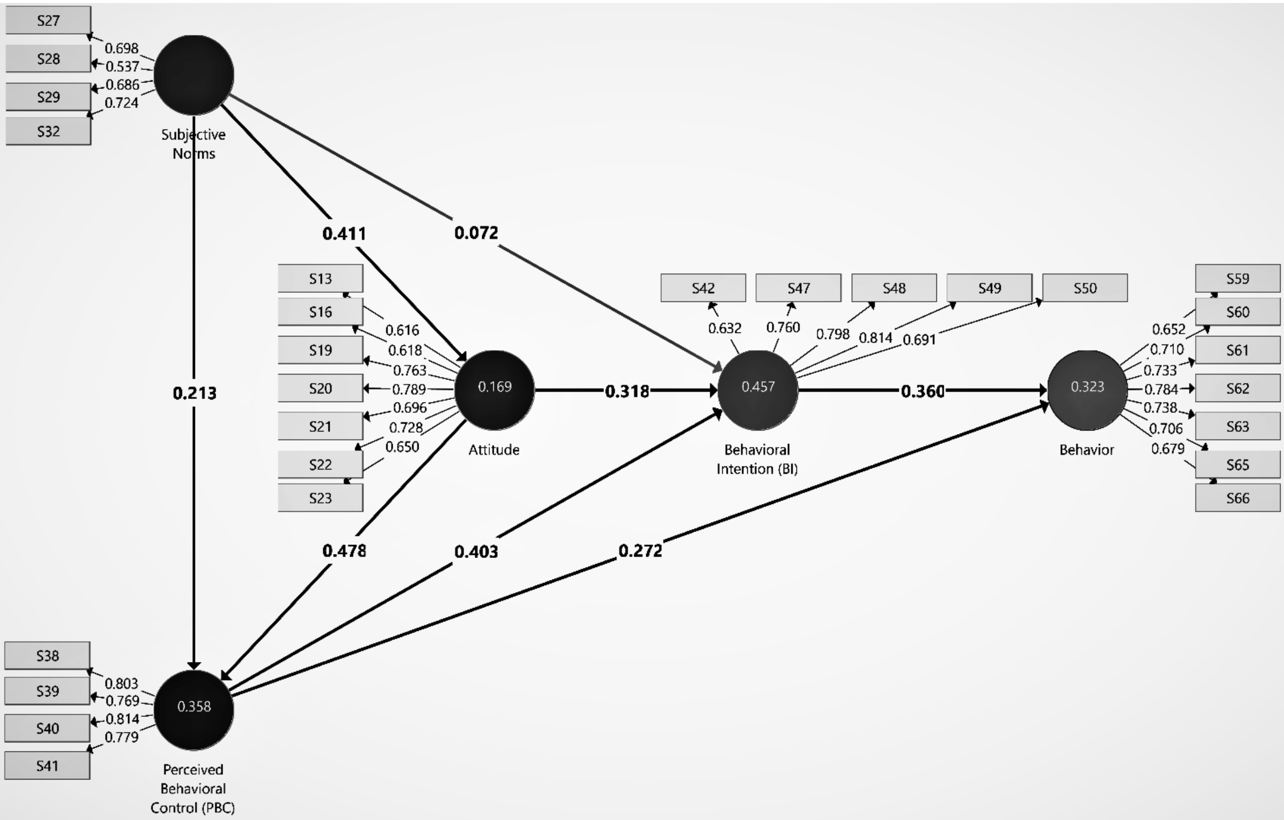

Figure 3. Measurement and structural model results of TPB-P (Model 1)

Table 2. The results of testing the first hypothesis in TPB-P (Model 1)

Hypothesis	Path coefficient (β)	Standard deviation	T Statistics (O/SD)	*P* value	Result
Attitude -> BI	0.318	0.051	6.240	0.000	**
Attitude -> PBC	0.478	0.049	9.856	0.000	**
BI -> Behavior	0.360	0.061	5.904	0.000	**
PBC -> Behavior	0.272	0.058	4.680	0.000	**
PBC -> BI	0.403	0.053	7.571	0.000	**
Subjective norms -> Attitude	0.411	0.046	8.925	0.000	**
Subjective norms -> BI	0.072	0.055	1.303	0.193	ns
Subjective norms -> PBC	0.213	0.049	4.319	0.000	**

Abbreviations: BI, behavioral intention; PBC, perceived behavioral control.
** Significant at $P<0.01$ (confirmed hypotheses); ns: not significant.

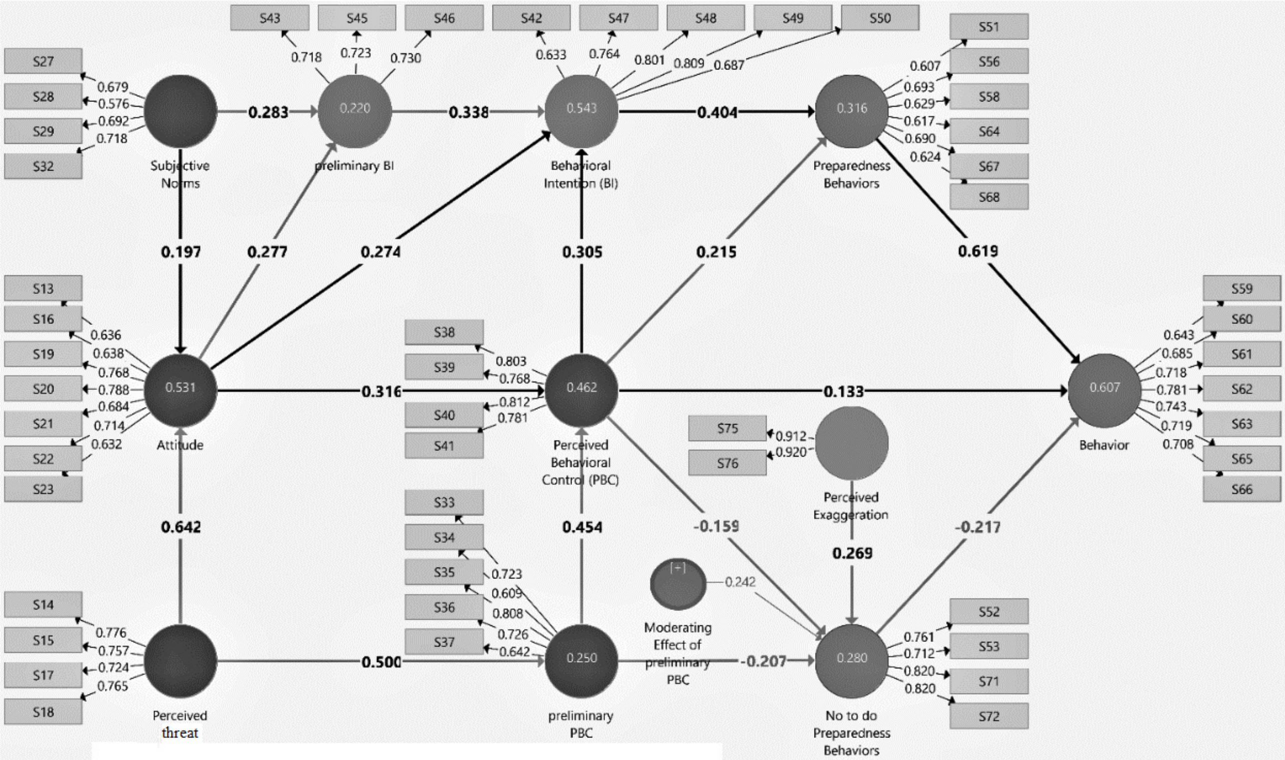

Figure 4. Measurement and structural model results of the ETPB-P (Model 2)

Table 3. The second hypothesis testing extended TPB (ETPB-P) (Model 2)

Hypothesis	Path coefficient (β)	Standard deviation	T statistics (O/SD)	*P* values
Attitude -> BI	0.274	0.049	5.566	0.000[a]
Attitude -> PBC	0.316	0.058	5.400	0.000[a]
Attitude -> preliminary BI	0.277	0.054	5.167	0.000[a]
BI -> Preparedness behaviors	0.404	0.055	7.332	0.000[a]
Moderating effect of preliminary PBC -> No to do preparedness behaviors	0.242	0.045	5.437	0.000[a]
No to do preparedness behaviors -> Behavior	-0.217	0.035	6.160	0.000[b]
PBC -> Behavior	0.133	0.041	3.273	0.001[a]
PBC -> BI	0.305	0.051	5.973	0.000[a]
PBC -> No to do preparedness behaviors	-0.159	0.065	2.461	0.014[b]
PBC -> Preparedness behaviors	0.215	0.056	3.800	0.000[a]
Perceived threat -> Attitude	0.642	0.037	17.558	0.000[a]
Perceived threat -> preliminary PBC	0.500	0.045	11.002	0.000[a]
Perceived exaggeration -> No to do preparedness behaviors	0.269	0.049	5.515	0.000[a]
Preparedness behaviors -> Behavior	0.619	0.041	15.049	0.000[a]
Subjective norms -> Attitude	0.197	0.041	4.808	0.000[a]
Subjective norms -> preliminary BI	0.283	0.053	5.353	0.000[a]
Preliminary BI -> BI	0.338	0.046	7.292	0.000[a]
Preliminary PBC -> No to do preparedness behaviors	-0.207	0.069	3.018	0.003[b]
Preliminary PBC -> PBC	0.454	0.058	7.758	0.000[a]

Abbreviations: BI, behavioral intention; PBC, perceived behavioral control.
[a] Positive and Significant; [b] Negative and significant.

preliminary BI (i.e., initial inclination or predisposition of an individual towards engaging in a specific behavior), and no to do preparedness behaviors (i.e., intention to refrain from engaging in preparedness behaviors).

In the second model (Figure 4), direct paths to intention originated from preliminary BI ($P<0.001$), attitude ($P<0.001$), and perceived control ($P<0.001$). Subjective norms, however, exhibited an indirect path through attitude ($P<0.001$) and preliminary BI ($P<0.001$). Together, these constructs can predict approximately 54% of the intention to engage in Ps use safety behavior ($R^2=0.543$) (Figure 4). All causal relationships in the visual model (Figure 4) were verified and confirmed. The lines between variables in this model represent significant relationships ($P<0.01$).

The study confirmed hypotheses that there are relationships between perceived threat or perceived exaggeration of health-related messages and constructs of the TPB. A standardized regression coefficient β, which estimates the number of standard deviations of change in the outcome variable for a one standard deviation unit change in the predictor variable while controlling for other predictors (51), was used to quantify this relationship. The effect size of a coefficient β is categorized as small for effect sizes between 0.10-0.29, medium for effect sizes between 0.30-0.49, and large for effect sizes of 0.50 or greater (49,52). The beta coefficient values of the two relationships mentioned above were found to be large.

Behavioral intention path

A more concise model was developed by combining perceived threat and perceived exaggeration of health-related messages into the TPB, which maintained the previous relationships and confirmed the previous hypotheses (Figure 4). The results showed positive and significant relationships between all variables (Table 3), except for preliminary PBC to no to do preparedness behaviors ($\beta=-0.207$, $t=3.018$), PBC to no to do preparedness behaviors ($\beta=-0.159$, $t=2.461$), and no to do preparedness behaviors to behavior ($\beta=-0.217$, $t=6.160$) were negative and significant (Table 3). Together, these variables in the ETPB-P model predicted approximately 60% of farmers' safety behavior in Ps use ($R^2=0.607$).

All indirect paths in model 2 had significant specific indirect effects, except for the second indirect path (Subjective norms to attitude to PBC to no to do preparedness behaviors to behavior), which was not significant.

Measurement model and path model analysis

For consistency reliability, Cronbach's alpha was calculated to be 0.748, and average rho_A was 0.753. Only one item had a value below 0.6 for Cronbach's alpha and rho_A, while the other items were above 0.7. Factor loading for each construct was analyzed, and the average of reflective indicators was 0.723. One indicator had a value below 0.6, 18 were between 0.6 and 0.7, and 32 were above 0.7. Average CR was 0.842, and the constructs ranged from 0.762 to 0.912. The AVE was 0.552, with only four of them having an average of 0.461, which were between 0.4 and 0.5, while the others were above 0.5. Despite some variables having a loading value below the threshold, according to Shrestha, the convergent validity of the construct is still adequate when the AVE was less than 0.5, and CR was higher than 0.6. Due to this reason and the fact that the panel of experts emphasized the existence of these variables, it was decided to keep them (53).

ETPB-P structural model

Table 3 and Figure 4 display the test results and coefficients for the second hypothesis tests. Additionally, Table 4 presents β and t-statistics. Based on the t-statistic and path coefficients, all hypotheses were confirmed. PLS estimation results for the structural model, including the R^2 values for the endogenous variables, path coefficient values, and item loadings for the research constructs, are illustrated in Figure 4.

ETPB-P discriminant validity

Discriminant validity was accepted with the Fornell-Larcker criterion (except for two very close cases) (48), as shown in Table 4.

Table 4. Discriminant validity values of ETPB-P using Fornell-Larcker criterion

	A	B	C	D	E	F	G	H	I	J	K	L
Attitude	**0.697**											
Perceived threat	**0.705**	**0.756**										
Behavior	0.477	0.354	**0.715**									
Preparedness behaviors	0.447	0.328	**0.732**	**0.644**								
BI	0.578	0.481	0.524	0.536	**0.742**							
Moderating effect of preliminary PBC	-0.183	-0.131	-0.188	-0.221	-0.134	**0.575**						
No to do preparedness behaviors	-0.396	-0.311	-0.407	-0.236	-0.269	0.258	**0.78**					
PBC	0.564	0.433	0.491	0.463	0.613	-0.032	-0.331	**0.791**				
Perceived exaggeration	-0.196	-0.259	-0.105	-0.101	-0.193	0.071	0.345	-0.124	**0.916**			
Subjective norms	0.401	0.318	0.324	0.399	0.363	-0.086	-0.201	0.403	-0.107	**0.668**		
Preliminary BI	0.391	0.311	0.375	0.396	0.584	-0.098	-0.161	0.455	-0.203	0.395	**0.723**	
Preliminary PBC	0.548	0.5	0.365	0.318	0.503	0.089	-0.334	0.627	-0.183	0.461	0.423	**0.705**

Abbreviations: BI, behavioral intention; PBC, perceived behavioral control.

Overall model fit
The SRMR value for this model was 0.072, which is considered a good fit as the value is less than 0.10 or even 0.08. The GoF value obtained for the complete model was 0.471, exceeding the cut-off value of 0.36 for large effect sizes of R^2. This indicates that the model performed well compared to the baseline values defined earlier.

Discussion
The objective of this study was to investigate the factors associated with the Ps use among farmers in Khuzestan, Iran. The TPB by Ajzen (22) was employed as the theoretical framework to examine the relationship between TPB variables and BI. All TPB variables, except for subjective norms, were significantly associated with BI. The TPB model accounted for 32% of the variance in Ps use behavior.

Furthermore, perceived threat and perceived exaggeration of health-related messages were identified as significant factors related to the TPB constructs. Therefore, to enhance the predictive power of the TPB model concerning farmers' intention and behavior in Ps use, these two variables could be integrated to develop an improved version of the TPB, called ETPB-P. The ETPB-P model showed stronger predictive power than the original TPB in predicting intention and behavior in Ps use among farmers, confirming the findings of previous studies and highlighting the benefits of expanding existing models to improve their efficacy in practical applications (18,31). For example, adding new constructs has been found to increase the explanatory power of the TPB in explaining safety behavior (7,18), which is consistent with the results of this study. Based on the findings of the present study, future research on Ps use behavior could integrate the ETPB-P variables, i.e., perceived threat and perceived exaggeration of health-related messages, to provide a more comprehensive understanding of the determinants of Ps use behavior among farmers.

TPB model
The TPB construct of subjective norms had an indirect relationship with BI through attitude and PBC. This finding is in line with previous research done in Iran on Ps use behavior of farmers, which found that subjective norms did not predict intentions (2). The weak relationship between subjective norms and intentions is a well-known limitation of the TPB (54). This is because intentions are heavily influenced by personal factors such as attitudes and PBC (55) and because the construct of subjective norms needs expansion into a multidimensional construct (56). The incorporation of new variables, as suggested in this study, can increase the explanatory power of the original TPB model, emphasizing the need for additional research to explain the Ps use behavior among farmers.

TPB-P and ETPB-P model
The two models, TPB-P and ETPB-P, exhibited satisfactory validity criteria, which is consistent with previous studies that have used TPB or other health behavior theories and models to assess health behavior and environmental health education and promotion (57-59).

In the TPB-P model, attitude was found to be the strongest predictor of PBC. According to this model, the performance of a behavior is influenced by the availability of resources and the ability to overcome barriers. Individuals who perceive more resources and fewer obstacles tend to have a higher PBC, leading to stronger intentions to perform a specific behavior. However, individuals may intend to change their health behaviors, but their daily environment may not facilitate these behaviors (60). Recent studies have suggested that an individual's intentions to engage in behavior are lower if they perceive little control over that behavior, even if they have a positive attitude (29). This finding is consistent with the argument that PBC plays a more significant role than attitudes in predicting intentions. Understanding this mechanism will facilitate the implementation of policies and educational instructions to promote farmers' healthy behavior.

In the ETPB-P model, perceived threat was found to be the strongest predictor of attitude. This means that to achieve the desired attitude, more emphasis should be placed on perceived threat. Numerous studies have reported that perceived threat is an essential factor in influencing protective behavior (61). Health risk messages typically focus on making individuals think about actual threats to their health (25). Therefore, if farmers perceive themselves to be vulnerable to the risks of pesticides, they become fearful and motivated to act. Thus, the greater the perceived threat, the stronger the motivation to take action (25).

Model differences
This study aimed to investigate the predictability of farmers' occupational behavior in Ps use using an extended version of the TPB. The extended TPB of the present study could predict 60% of the variance in farmers' occupational behavior. In contrast, Bagheri et al (2) found that the three constructs of the TPB (i.e., attitudes, subjective norms, and PBC) explained 81.9% of the variance in farmers' behavior in safe Ps use. These differences in findings in the explanatory power of the TPB may be influenced by factors such as geographical and cultural differences, as well as the type of crop cultivated.

Geographical location has a profound impact on culture, attitudes, beliefs, and behavior (62). Cultural differences, defined as how norms and values of a society differ from those of other societies (63), may also affect farmers' behavior. Normative influence has been shown to consistently affect perceptions and actions (64), and behavior can be affected by cultural factors, including norms and beliefs.

The type of crop cultivated may also have an impact on the predictability of farmers' occupational behavior. This study included only vegetable farmers, while the study of Bagheri et al (2) included all types of farmers. As different crops require different numbers of pesticide applications with different pesticides in terms of toxicity, the type of crop cultivated may affect the behavior in Ps use (65).

Taken together, these findings suggest that spatial components and the type of cultivated crop may influence the predictability of farmers' occupational behavior by the TPB model. It is important to note that training can be a valuable intervention for reducing farmers' exposure to Ps, which highlights the need for designing and implementing effective training programs in this field (65).

The ETPB-P model demonstrated stronger predictability of farmers' Ps use behavior compared to the TPB-P model, suggesting the need to incorporate variables such as perceived threat and perceived exaggeration of health-related messages in the original TPB. These variables have been shown to increase the explanatory power of the original model in explaining safety behavior, as suggested in previous literature (7,18).

The inclusion of perceived threat in the model aligns with previous literature, as it has been shown to predict attitudes and PBC (66). Such findings support the notion that increasing perceived threat and PBC can positively affect farmers' intentions and engagement in protective behaviors when using pesticides (67).

Additionally, the study confirmed prior research that perceived exaggeration of health-related messages is associated with reduced intentions to engage in safety behaviors (68). The incorporation of these constructs can further improve the design and implementation of interventions aimed at addressing farmers' use of Ps.

Implications

Several recent studies have applied the TPB to investigate factors influencing pro-environmental BI, such as water conservation (27), green purchasing (28), and climate change action (29). The present study expands the use of TPB to examine health behavior among farmers, making a significant contribution to the knowledge base regarding the application of TPB to the use of Ps.

The findings of this study offer practical suggestions for policymakers and practitioners in managing farmers' behavior in Ps use in agriculture. Specifically, combining perceived threat and perceived exaggeration of health-related messages with TPB may be a more effective approach to promoting healthy BI among farmers. It is important to consider the strongest predictors in tailoring media messages and designing and implementing educational programs in this area.

Strengths and limitations of the study

To the best of the authors' knowledge, no prior study has examined the Ps use behavior among farmers using the ETPB-P model. The TPB-P model and ETPB-P model proposed in this study can serve as a framework for planning, implementing, and evaluating occupational health education and promotion programs. However, this study has certain limitations. The cross-sectional nature of the data analysis prevents causal inference. Future studies are recommended to use longitudinal surveys or experimental designs to establish causality. Additionally, some variables had loadings below the designated threshold levels, indicating the need for further evaluation of the measurement model using more restrict criteria. Lastly, as this study focused only on vegetable farmers, the results may not be generalizable to all farmers. Therefore, additional research on other agricultural products is recommended.

Conclusion

This study aimed to identify factors associated with behavior in Ps use among farmers of Khuzestan using the TPB framework and an extended version of the TPB, called ETPB-P, which included perceived threat and perceived exaggeration of health-related messages as additional variables to the original model. Both models exhibited favorable validation criteria. The ETPB-P demonstrated higher explanatory power of intention and behavior related to Ps use compared to the TPB-P model. Perceived threat was found to be the strongest predictor of attitude in the ETPB-P model. The study makes a valuable contribution to existing research by incorporating new variables, i.e., perceived threat and perceived exaggeration of health-related messages, into the TPB to better understand farmers' behavior in Ps use. The extended TBP (ETPB-P) model can serve as a useful framework for designing relevant occupational health promotion programs that could improve the safety behavior of farmers in Ps use. These should focus on safe pesticide handling training, personal protective equipment access, and fostering collaboration between researchers, policymakers, and agricultural communities. Future research should explore ETPB-P's effectiveness in guiding interventions for sustainable agricultural practices.

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Competing interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. CAD is an editorial board member of the International Journal of Pest Management.

Ethical issues

The Ethics Committee of Ahvaz Jundishapur University of Medical Sciences, Ahvaz, Iran, approved the study (Registration No: IR.AJUMS.REC.1400.573). Written informed consent was obtained from all participants, and all methods adhered to relevant guidelines and regulations.

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References

1. Sheeran P. Intention—behavior relations: a conceptual and empirical review. Eur Rev Soc Psychol. 2002;12(1):1-36. doi: 10.1080/14792772143000003.
2. Bagheri A, Emami N, Damalas CA. Farmers' behavior towards safe pesticide handling: an analysis with the theory of planned behavior. Sci Total Environ. 2021;751:141709. doi: 10.1016/j.scitotenv.2020.141709.
3. Damalas CA, Eleftherohorinos IG. Pesticide exposure, safety issues, and risk assessment indicators. Int J Environ Res Public Health. 2011;8(5):1402-19. doi: 10.3390/ijerph8051402.
4. García-García CR, Parrón T, Requena M, Alarcón R, Tsatsakis AM, Hernández AF. Occupational pesticide exposure and adverse health effects at the clinical, hematological and biochemical level. Life Sci. 2016;145:274-83. doi: 10.1016/j.lfs.2015.10.013.
5. Baldi I, Lebailly P, Rondeau V, Bouchart V, Blanc-Lapierre A, Bouvier G, et al. Levels and determinants of pesticide exposure in operators involved in treatment of vineyards: results of the PESTEXPO study. J Expo Sci Environ Epidemiol. 2012;22(6):593-600. doi: 10.1038/jes.2012.82.
6. Bondori A, Bagheri A, Allahyari MS, Damalas CA. Pesticide waste disposal among farmers of Moghan region of Iran: current trends and determinants of behavior. Environ Monit Assess. 2018;191(1):30. doi: 10.1007/s10661-018-7150-0.
7. Bagheri A, Emami N, Damalas CA, Allahyari MS. Farmers' knowledge, attitudes, and perceptions of pesticide use in apple farms of northern Iran: impact on safety behavior. Environ Sci Pollut Res Int. 2019;26(9):9343-51. doi: 10.1007/s11356-019-04330-y.
8. Damalas CA. Understanding benefits and risks of pesticide use. Sci Res Essays. 2009;4(10):945-9.
9. Bondori A, Bagheri A, Damalas CA, Allahyari MS. RETRACTED: Use of personal protective equipment towards pesticide exposure: farmers' attitudes and determinants of behavior. Sci Total Environ. 2018;639:1156-63. doi: 10.1016/j.scitotenv.2018.05.203.
10. Huici O, Skovgaard M, Condarco G, Jørs E, Jensen OC. Management of empty pesticide containers-a study of practices in Santa Cruz, Bolivia. Environ Health Insights. 2017;11:1178630217716917. doi: 10.1177/1178630217716917.
11. Damalas CA, Telidis GK, Thanos SD. Assessing farmers' practices on disposal of pesticide waste after use. Sci Total Environ. 2008;390(2-3):341-5. doi: 10.1016/j.scitotenv.2007.10.028.
12. Aldosari F, Mubushar M, Baig MB. Assessment of farmers knowledge on pesticides and trainings on pesticide waste management in central Punjab-Pakistan. J Exp Biol Agric Sci. 2018;6(1):168-75. doi: 10.18006/2018.6(1).168.175.
13. Hurtig AK, San Sebastián M, Soto A, Shingre A, Zambrano D, Guerrero W. Pesticide use among farmers in the Amazon basin of Ecuador. Arch Environ Health. 2003;58(4):223-8. doi: 10.3200/aeoh.58.4.223-228.
14. Loloei M, Zolala F, Razzaghi A. Farmers' pesticide using behaviors: a case study on pistachio farms in Kerman, Iran. Health Scope. 2014;3(2):e14101. doi: 10.17795/jhealthscope-14101.
15. Jaeken P, Debaer C. Risk of water contamination by plant protection products (PPP) during pre-and post-treatment

operations. Annual Review of Agricultural Engineering. 2005;4(1):93-114.
16. Mubushar M, Aldosari FO, Baig MB, Alotaibi BM, Khan AQ. Assessment of farmers on their knowledge regarding pesticide usage and biosafety. Saudi J Biol Sci. 2019;26(7):1903-10. doi: 10.1016/j.sjbs.2019.03.001.
17. Shams A, Vedadi E, Ahmadi Z. Study of farmers' attitude towards sustainable agriculture and its relation with their chemical input use in Asadabad township. Iranian Agricultural Extension and Education Journal. 2015;11(1):197-210. [Persian].
18. Rezaei R, Safa L, Ganjkhanloo MM. Understanding farmers' ecological conservation behavior regarding the use of integrated pest management- an application of the technology acceptance model. Glob Ecol Conserv. 2020;22:e00941. doi: 10.1016/j.gecco.2020.e00941.
19. Ghobadi S, Chizari M, Sedeghi H. The analysis of farmer's behaviour and strategies in dealing with drought (the case study: Kermanshah township). Regional Planning. 2016;6(21):143-54. [Persian].
20. Bagheri A, Bondori A, Allahyari MS, Damalas CA. Modeling farmers' intention to use pesticides: an expanded version of the theory of planned behavior. J Environ Manage. 2019;248:109291. doi: 10.1016/j.jenvman.2019.109291.
21. Armitage CJ, Christian J. From attitudes to behaviour: basic and applied research on the theory of planned behaviour. Curr Psychol. 2003;22(3):187-95. doi: 10.1007/s12144-003-1015-5.
22. Ajzen I. The theory of planned behavior. Organ Behav Hum Decis Process. 1991;50(2):179-211. doi: 10.1016/0749-5978(91)90020-t.
23. Rezaei R, Seidi M, Karbasioun M. Pesticide exposure reduction: extending the theory of planned behavior to understand Iranian farmers' intention to apply personal protective equipment. Saf Sci. 2019;120:527-37. doi: 10.1016/j.ssci.2019.07.044.
24. Ajzen I. The theory of planned behavior: frequently asked questions. Hum Behav Emerg Technol. 2020;2(4):314-24. doi: 10.1002/hbe2.195.
25. Witte K, Meyer G, Martell D. Effective Health Risk Messages: A Step-by-Step Guide. SAGE Publications; 2001. doi: 10.4135/9781452233239.
26. Witte K. Fear control and danger control: a test of the extended parallel process model (EPPM). Commun Monogr. 1994;61(2):113-34. doi: 10.1080/03637759409376328.
27. Lam SP. Predicting intention to save water: theory of planned behavior, response efficacy, vulnerability, and perceived efficiency of alternative solutions. J Appl Soc Psychol. 2006;36(11):2803-24. doi: 10.1111/j.0021-9029.2006.00129.x.
28. Ho SS, Liao Y, Rosenthal S. Applying the theory of planned behavior and media dependency theory: predictors of public pro-environmental behavioral intentions in Singapore. Environ Commun. 2015;9(1):77-99. doi: 10.1080/17524032.2014.932819.
29. Lin SP. The gap between global issues and personal behaviors: pro-environmental behaviors of citizens toward climate change in Kaohsiung, Taiwan. Mitig Adapt Strateg Glob Chang. 2013;18(6):773-83. doi: 10.1007/s11027-012-9387-1.
30. Xia N, Xie Q, Hu X, Wang X, Meng H. A dual perspective on risk perception and its effect on safety behavior: a moderated mediation model of safety motivation, and supervisor's and coworkers' safety climate. Accid Anal Prev. 2020;134:105350. doi: 10.1016/j.aap.2019.105350.
31. Yuen KF, Li KX, Ma F, Wang X. The effect of emotional appeal on seafarers' safety behaviour: an extended health belief model. J Transp Health. 2020;16:100810. doi: 10.1016/j.jth.2019.100810.
32. Afshari M, Poorolajal J, Rezapur-Shahkolai F, Assari MJ, Karimi-Shahanjarini A. Which factors influence farmers' use of protective measures during pesticides exposure? Workplace Health Saf. 2019;67(7):338-49. doi: 10.1177/2165079919827042.
33. IBM SPSS. IBM SPSS Statistics for Windows. Armonk, New York: IBM SPSS. 2013.
34. Huang Y, Luo X, Tang L, Yu W. The power of habit: does production experience lead to pesticide overuse? Environ Sci Pollut Res Int. 2020;27(20):25287-96. doi: 10.1007/s11356-020-08961-4.
35. Ringle CM, Wende S, Becker JM. SmartPLS 3. Bönningstedt: SmartPLS GmbH; 2015.
36. Hair JF, Matthews LM, Matthews RL, Sarstedt M. PLS-SEM or CB-SEM: updated guidelines on which method to use. International Journal of Multivariate Data Analysis. 2017;1(2):107-23. doi: 10.1504/ijmda.2017.087624.
37. Hair JF, Risher JJ, Sarstedt M, Ringle CM. When to use and how to report the results of PLS-SEM. Eur Bus Rev. 2019;31(1):2-24. doi: 10.1108/ebr-11-2018-0203.
38. Lomax RG. A Beginner's Guide to Structural Equation Modeling. New York: Psychology Press; 2004. doi: 10.4324/9781410610904.
39. Sarstedt M, Ringle CM, Hair JF. Partial least squares structural equation modeling. In: Homburg C, Klarmann M, Vomberg A, eds. Handbook of Market Research. Cham: Springer; 2021. p. 587-632. doi: 10.1007/978-3-319-57413-4_15.
40. Herjanto H, Amin M. Repurchase intention: the effect of similarity and client knowledge. Int J Bank Mark. 2020;38(6):1351-71. doi: 10.1108/ijbm-03-2020-0108.
41. Mohammad J, Quoquab F, Idris F, Al Jabari M, Wishah R. The mediating role of overall fairness perception: a structural equation modelling assessment. Employee Relations: The International Journal. 2019;41(3):614-36. doi: 10.1108/er-10-2017-0243.
42. Amin M, Aldakhil AM, Wu C, Rezaei S, Cobanoglu C. The structural relationship between TQM, employee satisfaction and hotel performance. Int J Contemp Hosp Manag. 2017;29(4):1256-78. doi: 10.1108/ijchm-11-2015-0659.
43. Hair JF, Sarstedt M, Ringle CM, Mena JA. An assessment of the use of partial least squares structural equation modeling in marketing research. J Acad Mark Sci. 2012;40(3):414-33. doi: 10.1007/s11747-011-0261-6.
44. Mohammadi F, Mahmoodi F. Factors affecting acceptance and use of educational Wikis: using technology acceptance model (3). Interdiscip J Virtual Learn Med Sci. 2019;10(1):5-9. doi: 10.5812/ijvlms.87484.
45. Henseler J, Dijkstra TK, Sarstedt M, Ringle CM, Diamantopoulos A, Straub DW, et al. Common beliefs and reality about PLS: comments on Rönkkö and Evermann (2013). Organ Res Methods. 2014;17(2):182-209. doi: 10.1177/1094428114526928.
46. Hu LT, Bentler PM. Cutoff criteria for fit indexes in covariance structure analysis: conventional criteria versus new alternatives. Struct Equ Modeling. 1999;6(1):1-55. doi: 10.1080/10705519909540118.

47. Tenenhaus M, Amato S, Esposito Vinzi V. A global goodness-of-fit index for PLS structural equation modelling. Proceedings of the XLII SIS Scientific Meeting. 2004;1(2):739-42.
48. Fornell C, Larcker DF. Evaluating structural equation models with unobservable variables and measurement error. J Mark Res. 1981;18(1):39-50. doi: 10.1177/002224378101800104.
49. Cohen J. Statistical Power Analysis for the Behavioral Sciences. Routledge; 2013.
50. Wetzels M, Odekerken-Schröder G, Van Oppen C. Using PLS path modeling for assessing hierarchical construct models: guidelines and empirical illustration. MIS Q. 2009;33(1):177-95. doi: 10.2307/20650284.
51. Nieminen P. Application of standardized regression coefficient in meta-analysis. BioMedInformatics. 2022;2(3):434-58. doi: 10.3390/biomedinformatics2030028.
52. Fey CF, Hu T, Delios A. The measurement and communication of effect sizes in management research. Manag Organ Rev. 2023;19(1):176-97. doi: 10.1017/mor.2022.2.
53. Shrestha N. Factor analysis as a tool for survey analysis. Am J Appl Math Stat. 2021;9(1):4-11. doi: 10.12691/ajams-9-1-2.
54. Armitage CJ, Conner M. Efficacy of the theory of planned behaviour: a meta-analytic review. Br J Soc Psychol. 2001;40(Pt 4):471-99. doi: 10.1348/014466601164939.
55. Ham M, Jeger M, Frajman Ivković A. The role of subjective norms in forming the intention to purchase green food. Econ Res Ekon Istraz. 2015;28(1):738-48. doi: 10.1080/1331677x.2015.1083875.
56. Morren M, Grinstein A. The cross-cultural challenges of integrating personal norms into the theory of planned behavior: a meta-analytic structural equation modeling (MASEM) approach. J Environ Psychol. 2021;75:101593. doi: 10.1016/j.jenvp.2021.101593.
57. Pakpour AH, Zeidi IM, Emamjomeh MM, Asefzadeh S, Pearson H. Household waste behaviours among a community sample in Iran: an application of the theory of planned behaviour. Waste Manag. 2014;34(6):980-6. doi: 10.1016/j.wasman.2013.10.028.
58. Zhang D, Huang G, Yin X, Gong Q. Residents' waste separation behaviors at the source: using SEM with the theory of planned behavior in Guangzhou, China. Int J Environ Res Public Health. 2015;12(8):9475-91. doi: 10.3390/ijerph120809475.
59. Abbasi A, Araban M, Heidari Z, Alidosti M, Zamani-Alavijeh F. Development and psychometric evaluation of waste separation beliefs and behaviors scale among female students of medical sciences university based on the extended parallel process model. Environ Health Prev Med. 2020;25(1):12. doi: 10.1186/s12199-020-00849-6.
60. Hardin-Fanning F, Ricks JM. Attitudes, social norms and perceived behavioral control factors influencing participation in a cooking skills program in rural Central Appalachia. Glob Health Promot. 2017;24(4):43-52. doi: 10.1177/1757975916636792.
61. Rattay P, Michalski N, Domanska OM, Kaltwasser A, De Bock F, Wieler LH, et al. Differences in risk perception, knowledge and protective behaviour regarding COVID-19 by education level among women and men in Germany. Results from the COVID-19 Snapshot Monitoring (COSMO) study. PLoS One. 2021;16(5):e0251694. doi: 10.1371/journal.pone.0251694.
62. Chen H, Lai K, He L, Yu R. Where you are is who you are? The geographical account of psychological phenomena. Front Psychol. 2020;11:536. doi: 10.3389/fpsyg.2020.00536.
63. Liu RW, Lapinski MK, Kerr JM, Zhao J, Bum T, Lu Z. Culture and social norms: development and application of a model for culturally contextualized communication measurement (MC3M). Front Commun. 2022;6:770513. doi: 10.3389/fcomm.2021.770513.
64. Rhodes N, Shulman HC, McClaran N. Changing norms: a meta-analytic integration of research on social norms appeals. Hum Commun Res. 2020;46(2-3):161-91. doi: 10.1093/hcr/hqz023.
65. Damalas CA, Koutroubas SD. Farmers' training on pesticide use is associated with elevated safety behavior. Toxics. 2017;5(3):19. doi: 10.3390/toxics5030019.
66. Murray DR, Schaller M. Threat (s) and conformity deconstructed: perceived threat of infectious disease and its implications for conformist attitudes and behavior. Eur J Soc Psychol. 2012;42(2):180-8. doi: 10.1002/ejsp.863.
67. Cauberghe V, De Pelsmacker P, Janssens W, Dens N. Fear, threat and efficacy in threat appeals: message involvement as a key mediator to message acceptance. Accid Anal Prev. 2009;41(2):276-85. doi: 10.1016/j.aap.2008.11.006.
68. Neureiter A, Stubenvoll M, Kaskeleviciute R, Matthes J. Trust in science, perceived media exaggeration about COVID-19, and social distancing behavior. Front Public Health. 2021;9:670485. doi: 10.3389/fpubh.2021.670485.