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SLR: Weight Analysis of Protection Motivation Theory

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Abstract. Protection Motivation Theory (PMT) has been effective in addressing a number of social behaviors. However, its literature review has not been exhaustive. As a result, the primary objective of this work is to contain a comprehensive analysis of recent advances in PMT in the generic domain, as well as a weighted review of the variables that aid in the theory's expansion. Following that, we independently assessed 138 papers published between 2014 and 2020 in 92 journals and 12 conferences. We discovered an astonishing increase in the number of publications over the last seven years throughout our analysis, indicating that the theory is consuming stability and promise in its application. Additionally, the weight analysis result was attributed to the diagrammatic portrayal of significant and non-significant associations in this study. Weight analysis indicated that coping-appraisal variables had a higher predictive validity than threat-appraisal variables, with self-efficacy being the most effective predictor. Apart from the standard constructs, the most often occurring and heavily weighted factors were Attitude and Subjective norm. Further, the inconsistency of the theory variables has been noted and the inclusion of moderators has been proposed accordingly in this study.

Keywords: Diagrammatic representation, moderator, PMT, systematic literature review, weight analysis

1. Introduction

Fear motivates people to respond to suggested changes, and this tactic has been used for more than 50 years. This fear might be imagined as a negative emotion generated by the risk that combines with a high level of anticipation (Floyd et al., 2000; Milne et al., 2000). Importantly, Rogers pioneered the Protection Motivation Theory (PMT) in 1975, which focused on these apprehension difficulties (Floyd et al., 2000). Indeed, PMT evolved from the Health Belief Model (Hsieh et al., 2016). Therefore, both PMT and HBM have the same philosophy of expectancy-value theory, as well as similar types of constructions (Hsieh et al., 2016; Floyd et al., 2000). Milne et al. (2000), on the other hand, have confirmed that using PMT is superior to HBM, TRA, and TPB because the theory has been systematically subjected to quantitative study. Furthermore, Karahoca et al. (2018) revealed that PMT outperforms behavior theories in terms of explanatory power. Finally, this theory may solve problems efficiently and resolve many societal problems that individuals can effectively implement (Westcott et al., 2017). As a result, it is worthwhile to review the theory.

Importantly, our study has certain advantages above the present literature. First and foremost, we discovered very few research publications that examined the PMT. Among these papers, Floyd et al. (2000), Milne et al. (2000) solely examined health-related papers, and Sommestad et al. (2015) examined information security-related papers. Therefore, all studies were domain-specific, and according to our concern, the generic performance of PMT has not been adequately investigated. However, according to Westcott et al. (2017), PMT can apply to any threat-related behavior. As a result, our review will provide insightful information about PMT adaptation to generic behavior. Second, Floyd et al. (2000), Milne et al. (2000), and Sommestad et al. (2015) were published almost 22, 22, and 7 years ago, respectively. As a result, new material has not been contributed to these articles, which will be addressed in our study through the exploration of the use and expansion of PMT. Finally, according to Floyd et al. (2000), a quantitative analysis of PMT is required since a quantitative analysis of the theory will evaluate the contribution of the PMT variables. Milne et al. (2000), on the other hand, emphasized that a quantitative analysis of PMT has not been attempted sufficiently. As a result, we will conduct quantitative analysis (weight analysis) to investigate the significance of PMT factors and external variables in the generic domain. Notably, none of the previously mentioned PMT review publications performed weight analysis in their research.

This study would be beneficial to readers and academics who are particularly interested in various psychological activities such as threat, fear, security, negative emotions, and so on. Furthermore, researchers who employ PMT to address many types of behaviors will benefit immensely from this research. Furthermore, it is widely expected that the weight analysis of the predictors will assist researchers in selecting the most appropriate factors for their individual-level investigations. The current growth analysis, on the other hand, will inspire scholars to add more to this theory. Furthermore, the weight analysis results of the predictors should influence and drive the development of business strategies by organizations, governments, and entrepreneurs.

2. Theoretical background

In this section, two topics will be discussed. At first, a brief overview of PMT will be provided. Afterward, the weight calculation process and its importance will be elaborated.

2.1. Overview of protection motivation theory

According to Mahmud et al. (2016), the mechanisms of cognitive mediation of PMT can be divided into two types, namely Threat and Coping appraisal (see Figure 1).

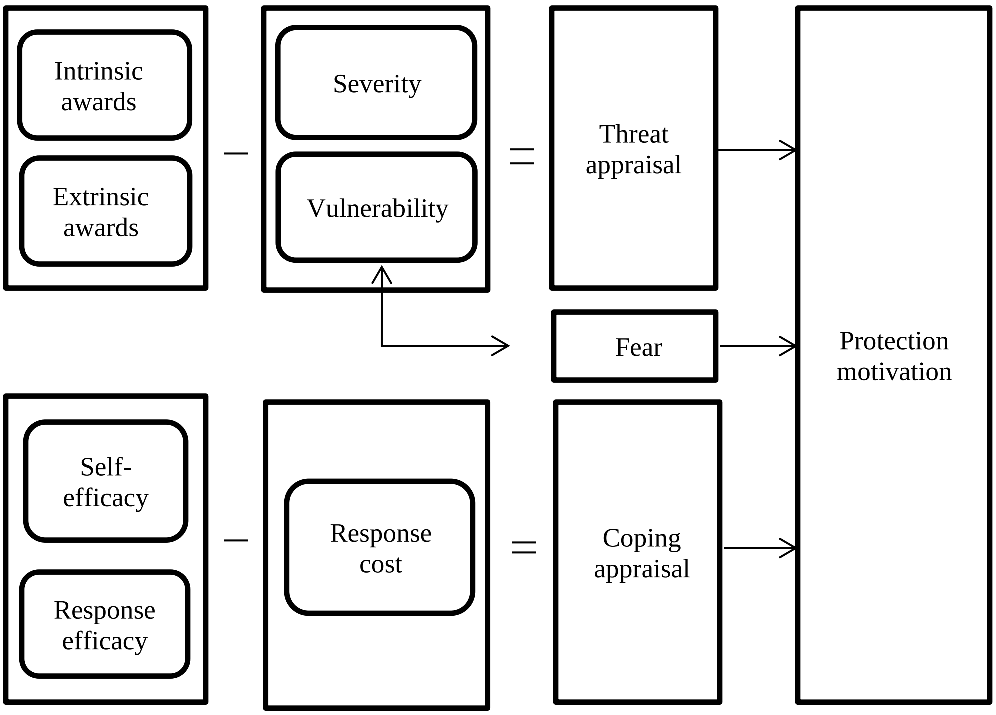

Fig. 1: Cognitive mediating processes (Floyd et al., 2000)

To begin, threat assessment refers to the process of evaluating components associated with the interpretation of risks or hazards. Furthermore, elements such as perceived severity and perceived vulnerability are incorporated in threat assessment. Indeed, when a person notices extreme vulnerability, the likelihood of performing protective behaviors increases. Perceived severity, on the other hand, examines how serious the person feels about the hazard's negative implications. Nonetheless, this

Reward variable is rarely examined because any recompense linked with unexecuted protective behavior can be repeated as a Response cost of Coping appraisal (Al-ghaith, 2016; Verkoeyen & Nepal, 2019).

Second, coping evaluation is associated with suggested preventive action, which examines a person's ability to cope with the hazard. A Coping evaluation also includes a discussion of three constructs: self-efficacy, response efficacy, and response cost. Initially, self-efficacy refers to the belief that one can or cannot carry out the specified preventive response. Response efficacy, on the other hand, denotes ideas about whether the proposed preventive strategy will be helpful in preventing or decreasing danger. Finally, response cost entails assumptions about how expensive a proposed preventative method will be to individuals. An example of a response cost is annoyance, overhead, difficulty, complexity, and so on (Al-ghaith, 2016; Verkoeyen & Nepal, 2019). Finally, the intention to execute the desirable behavior coming from these two assessment methods is the center of the theory 'Protection motivation,' which is generally equated to Behavioral intentions (Verkoeyen & Nepal, 2019).

2.2. Weight calculation and its importance

The weight is calculated by dividing the number of significant relationships by the total number of relationships. When a variable is given a weight, it is assumed to be a weighted variable. To determine the weight, we must first determine how many times a certain relationship between constructs has been investigated, and then determine how many of these correlations are significant. The weight value of a relationship between constructs is calculated by dividing the second data value by the first. Furthermore, the weight value will be between 0 and 1. In all of the publications that have been evaluated, this 0 and 1 imply that the association is non-significant and significant, respectively (Jeyaraj et al., 2006; Rana et al., 2015). Jeyaraj et al. (2006) further classified these independent variables as well-utilized (WU) or experimental (EXP). During the analysis, well-utilized variables are tested at least five times, while experimental variables are reviewed less than five times. When well-utilized variables achieve a weight value of at least 0.8, they are referred to as the best predictors (BP). On the other hand, when the experimental variables have a weight value of 1.0, they are referred to as promising predictors (PRO).

PMT is currently largely regarded as one of the most widely accepted theories, particularly in research addressing threat, security, and fear (Jansen & van Schaik, 2018; Srisawang et al., 2015). Furthermore, numerous studies have blended PMT with various theories and external factors to solve a variety of difficulties. Consider TAM (Al-Emran et al., 2020), TPB (Safa et al., 2015), and so on. However, the performance of these variables appears to differ based on the type of domains and difficulties. As a result, each variable's performance must be judged independently. According to Jeyaraj et al. (2006), researchers should identify compelling reasons to continue using such predictors. The authors also suggest that each variable be assigned a weight so that prior performance can be understood and model stability can be demonstrated. Another reason to conduct weight analysis is that the weights reflect an independent variable's predictive capacity (Jeyaraj et al., 2006). Furthermore, weight estimate and meta-analysis are more closely associated, because the greater the weight of the predictor variable, the more likely a quantitative study will be significant (Rana et al., 2015). Furthermore, the weight analysis might be used as a baseline for future studies to demonstrate their efficacy. In some cases, this allows researchers to see the convergence and divergence points.

3. Methodology

Our Systematic Literature Review (SLR) was conducted using these 8 steps (see Figure 2) as proposed by (Kitchenham & Charters, 2007; Ain et al., 2019):

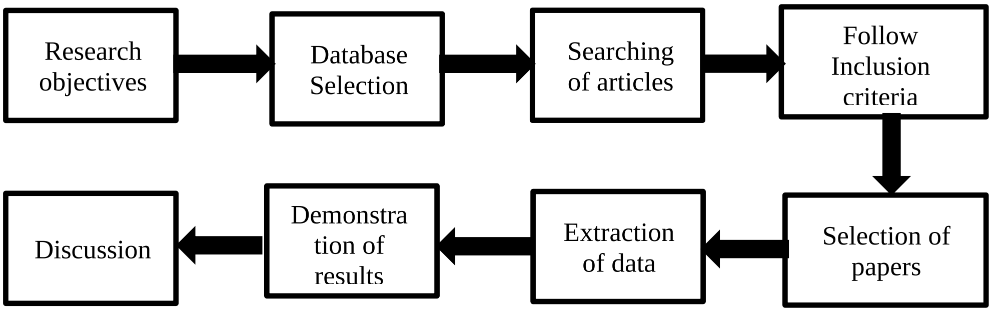

Fig. 2: Steps to be followed for SLR

The analysis approach started with stating the research objectives. The research objectives are as follows:

1. To explore the usage and growth of protection motivation theory at the individual level during the period 2014-2020.
2. To find out the variables that help to develop and extend protection motivation theory.
3. To perform weight analysis of corresponding variables towards Protection motivation, Intention, and Behavior.

Following (Alkawsi & Ali, 2018), the search was executed on 5 databases namely Scopus, ScienceDirect, Google Scholar, Taylors & Francis, and IEEE explore from August 02 to September 15, 2020. Afterward, the research exploration began with a search for articles related to PMT. Therefore, a relevant set of keywords and phrases was employed, such as “protection motivation”, “PMT”, “protection motivation theory/model/intention/behavior”, motivation theory/model/intention/behavior and “protection theory/model/intention/behavior”. Importantly, we set the following inclusion-exclusion criteria (see Table 1) for the SLR.

Table 1: Inclusion-exclusion criteria

No	Inclusion	Exclusion
1	Articles published between 2014-2020	Articles published before 2013
2	Articles published in the English language	Articles published in other languages
3	Academic journals and conference papers	Short papers, white papers, book chapters, case reports, review papers, editorials, and other secondary sources
4	Papers related to PMT and extended PMT	Any other IS theories and conceptual models
5	Results from structural equation modeling	Only results from pre-test, pilot test, measurement, technical model, etc.
6	The quantitative method	The qualitative method
7	Unit of analysis is individual	Other types of unit of analysis
8	Full-length articles	Not the full-length articles
9	Empirically tested	Not the empirically tested

Moreover, all of the 382 downloaded articles were inspected using the given 3 steps (see Figure 3) as followed by (Suppatvech et al., 2019):

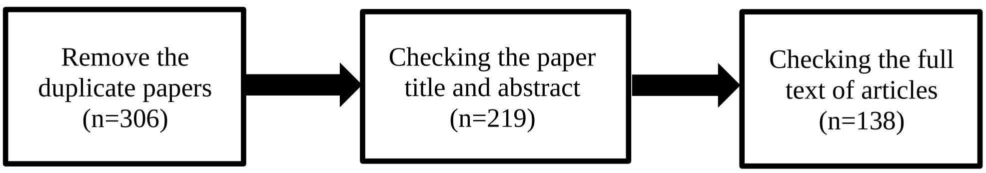

Fig. 3: Steps included for paper selection

Notably, the number of papers approved at each stage is indicated by the letter ‘n.' After the completion of the assessment, 138 articles were accepted for review from 92 journals and 12 conference papers. The flow diagram is reported in Fig. 4.

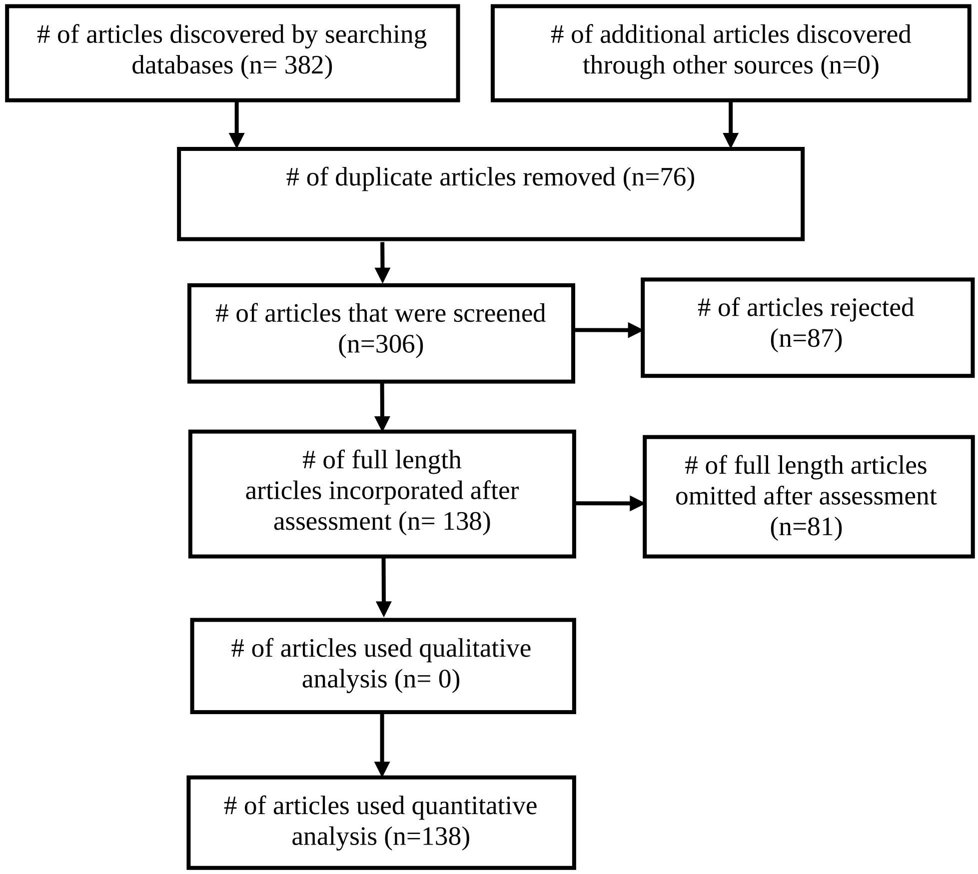

Fig. 4: Flow diagram

Finally, all the necessary data were extracted from the papers like the name of authors, publication year, country, sampling type, dependent construct, independent construct, moderators, variance, etc.

4. Results

The quantitative analysis of the paper revealed some interesting insights into publishing trends.

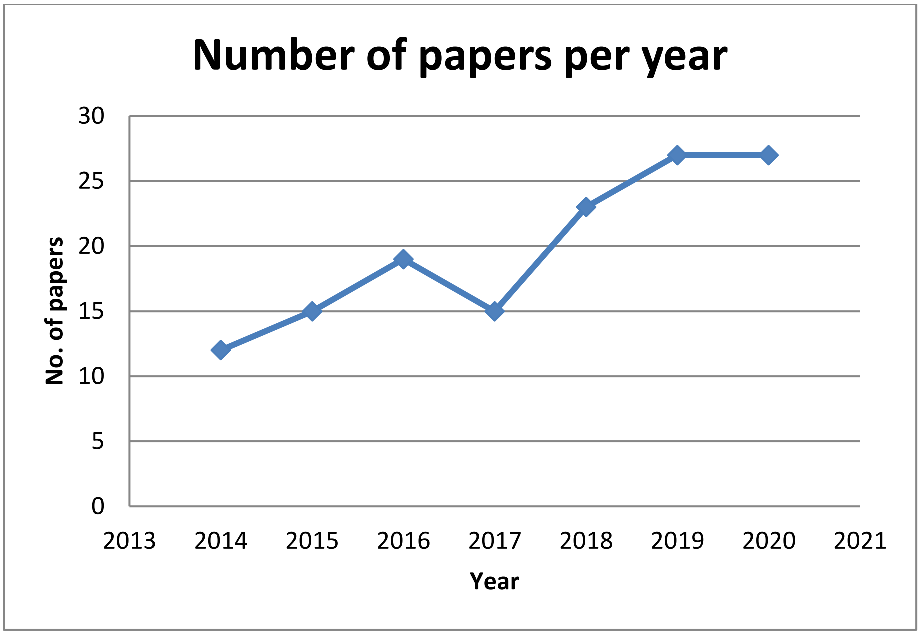

Fig. 5: Number of papers per year from 2014

If we disregard the decrease in 2017, the growth in the number of papers produced per year after 2013 could be seen as shown in Figure 5. The largest number of papers was produced in both 2019 and 2020, accounting for 39% of all papers. However, since our data collection ended in the middle of September 2020 and the results from the conferences were not updated for 2020, there were no significant numbers of publications that can be noticed for that year. Furthermore, as shown in Table 2, we discovered five categories of PMT applications in various nations, namely information security (64 papers), health (50 papers), environmental (18 papers), crime & threat (4 papers), and smart devices (2 papers). Indeed, this PMT was originally designed to address health-related issues, but it currently focuses on information security, followed by health and environmental concerns. It is worth noting that some papers have been written by writers from various countries. As a result, in some studies, multiple countries represent the same application. Therefore, the total number of applications exceeds the total number of publications.

Table 2: PMT application across the countries

No	Country	Information security	Health	Environ mental	Crime and Threat	Smart devices	Total
1	Australia	6	2	1	1		10
2	Austria		1				1
3	Belgium	1		1			2
4	Cameroon		1				1
5	Canada	2	3	1			6

6	China	3	7	7			17
7	Croatia	1					1
8	Czech Republic			1			1
9	Finland	3	2				5
10	France	2					2
11	Germany	1		1			2
12	Hong Kong	3	1				4
13	India	1					1
14	Indonesia	2			1		3
15	Iran		16	4			20
16	Kenya	1					1
17	Kuwait		1				1
18	Malaysia	4	1	1			6
19	Netherlands	4					4
20	New Zealand	1		1			2
21	Nigeria			1			1
22	Norway		1				1
23	Oman	3					3
24	Pakistan			1			1
25	Philippines		1		1		2
26	Saudi Arabia	1					1
27	Singapore		1				1
28	South Africa	1	1				2
29	South Korea	2	4	2		1	9
30	Sweden	1					1
31	Switzerland		1				1
32	Taiwan	4	2	2		1	9
33	Thailand		1		1		2
34	Turkey		1				1
35	United Kingdom	7	1	1			9
36	USA	29	7	3	1		40
37	Vietnam	1					1

We tried to collect the predictive variance of the focus variables from the papers. Unfortunately, some of the papers did not report the result. However, based on reported variance we have found the following:

Table 3: The predictive variance of intention, protection motivation, and behavior

No	Focus variable	Maximum variance	Minimum variance	Average variance
1	Intention	0.94	0.091	0.468
2	Protection motivation	0.7	0.198	0.473
3	Behavior	0.85	0.051	0.421

Table 3 shows that the variance ranges of Intention, Protection motive, and Behavior are 0.849, 0.502, and 0.799, respectively. Importantly, the variation of Willingness and Continuous Intention was regarded to be a component of Intention. In addition, we calculated the average variance by dividing the total reported variance (R^2) by the number of papers. Notably, the intention is defined as the degree to which an individual has established an intentional plan to engage in or refrain from engaging in specified potential behaviors. Furthermore, behavior is defined as the frequency and volume of technology use reported by the user (Amelia & Ronald, 2017). Finally, the desire to engage in desirable activity as a result of two evaluation methods is referred to as protective motivation, which is commonly related to behavioral intentions (Verkoeyen, & Nepal, 2019). The frequency of distinct independent variables utilized in PMT is now counted in the table below (see Table 4).

Table 4: Frequency of variables

No	Variables	Short-form	Count	No	Variables	Short-form	Count
1	Perceived self-efficacy	PSE	127	75	Perceived norm	PN	1
2	Perceived severity	PS	122	76	Perceived advantage	PAD	1
3	Perceived response efficacy	PRE	113	77	Personal innovativeness	PI	1
4	Perceived vulnerability	PV	89	78	Compatibility	COMP	1
5	Response cost	RC	89	79	Trialability	TRI	1
6	Rewards	RE	28	80	Image	IMG	1
7	Perceived threat susceptibility	PSUS	25	81	Personal health status	PHS	1
8	Attitude	ATT	23	82	Cost of compliance	COC	1
9	Subjective norm	SN	23	83	Cost of noncompliance	CON	1
10	Fear	Fear	20	84	Neutralization	NEU	1
11	Threat appraisal	TA	13	85	Perceived password effectiveness	PPE	1
12	Coping appraisal	CA	12	86	Learner control	LCON	1
13	knowledge	KN	9	87	Training performance	TPER	1
14	Perceived privacy	PRI	9	88	Stage	STG	1
15	Prior experience	PEX	9	89	National smartphone	CYPO	1

					cybersecurity policies		
16	Social Influence	SI	6	90	Top-management participation	TMG T	1
17	Perceived usefulness	PU	6	91	Computer skills	CSK	1
18	Perceived ease of use	PEOU	6	92	Psychological Capital	PSYC AP	1
19	Descriptive norms	DN	5	93	Familiarity	FAM	1
20	Perceived benefit	PB	5	94	Management quality	MGM T	1
21	Intrinsic reward	INRE	5	95	Safety Liability	SALI	1
22	Extrinsic reward	EXRE	5	96	Secondary Data Influence	SDF	1
23	Perceived risk	PRSK	4	97	Job security	JS	1
24	Perceived behavior control	PBC	4	98	Planning	PLAN	1
25	Protective behavior	PB	4	99	Incentives	INC	1
26	Perceived Effectiveness	PEF	3	10 0	Belief	BEL	1
27	Performance expectancy	PE	3	10 1	Previous incident	PIN	1
28	Uncertainty avoidance	UA	3	10 2	Sensitivity	SNSE	1
29	Information Overload	IO	3	10 3	Ubiquitous connectivity	UBC N	1
30	Perceived Value	PVA	2	10 4	Exhaustion	EXH	1
31	Perceived threat	PTH	3	10 5	System quality	SQ	1
32	Perceived competence	PCO M	3	10 6	Negative experience	NEXP	1
33	Sanctions	SANC	3	10 7	Provision of policy	PRPO	1
34	Perceived Security (Support)	PSS	3	10 8	Impact	IMP	1
35	Personal Responsibility	PRES	3	10 9	Likelihood	LIKE	1
36	Habit Strength	HSTR	3	11 0	Perceived Digital Mutualism Justice	JUST	1
37	Perceived barriers	PBAR	3	11 1	IT Support	SUPP	1
38	Cues to action	CTA	3	11 2	literacy	LIT	1

39	Experience	EXP	3	113	Obstacle	OBS	1
40	Sanction celerity	SC	3	114	Sanction certainty	SANCC	1
41	Locus of control	LC	2	115	Info-Quality	INFQ	1
42	Injunctive norms	IN	2	116	formal sanction certainty	FSC	1
43	Facilitating condition	FC	2	117	informal sanction certainty	ISC	1
44	CyberChondria	CCH	2	118	formal sanction severity	FSS	1
45	Organizational commitment	OC	2	119	informal sanction severity	ISS	1
46	Social support	SS	2	120	Hedonic motivation	HM	1
47	Normative faith	NF	2	121	Social environment	SOEN	1
48	Perceived relatedness	PREL	2	122	Task technology fit	TTF	1
49	Perceived autonomy	PAUTO	2	123	Patient activation measure	PAM	1
50	Response performance motivation	RPM	2	124	Emotional stability	EMS	1
51	Peer behavior	PBHV	2	125	Agreeableness	AGR	1
52	Collectivism	COL	2	126	Extraversion	EXTR	1
53	Programs	PROG	2	127	Openness	OPEN	1
54	Detection	DET	2	128	Perceived concurrency	PCON	1
55	Program	PROG	2	129	Perceived automaticity	PAUTOM	1
56	Exposure	EXPO	2	130	Community participation	COMPN	1
57	Effort expectancy	EE	2	131	Empowerment	EMPOW	1
58	Conscientiousness	CONS	2	132	Top Management Support	TMS	1
59	Psychological ownership	PSYO	2	133	Peer Pressure	PEPR	1
60	Awareness	AWARE	2	134	Organizational Climate	ORGC	1
61	Social appraisal	SA	2	135	Social cognitive attributes	SCA	1
62	Trust	TRU	1	136	Prior Physical Activity	PPA	1

63	Understanding	UND	1	137	Family income	FI	1
64	Power distance	PD	1	138	Personalization	PERN	1
65	Individualism vs collectivism	IVC	1	139	Threat awareness	TAWARE	1
66	Masculinity vs femininity	MVF	1	140	Countermeasure awareness	CAWARE	1
67	Online Information Source	OIS	1	141	Perceived Extraneous Circumstances	PEC	1
68	Collective efficacy	CE	1	142	Maladaptation	MAL	1
69	Perceived government support	PGS	1	143	Social distancing	SD	1
70	Security breach	SB	1	144	Perceived difficulty	PDI	1
71	Punishment severity	PUNS	1	145	Security breach	SBCL	1
72	Perceived probability	PPROB	1	146	Group norm	GN	1
73	Water quality safety concerns	WQSC	1	147	Exergaming	EXM	1
74	Anticipated regret	AR	1				

Table 4 shows that we have discovered a total of 147 independent variables from 138 studies. Aside from the standard PMT categories, Attitude (23 times), Subjective norm (23 times), Knowledge (9 times), Perceived privacy (9 times), Prior experience (9 times), Social Influence (6 times), Perceived utility (6 times), and Perceived Ease of use (6 times) were utilized more than 5 times. Only 22 variables were used five or more times, and 58.5% of the variables appeared only once in the studies we examined.

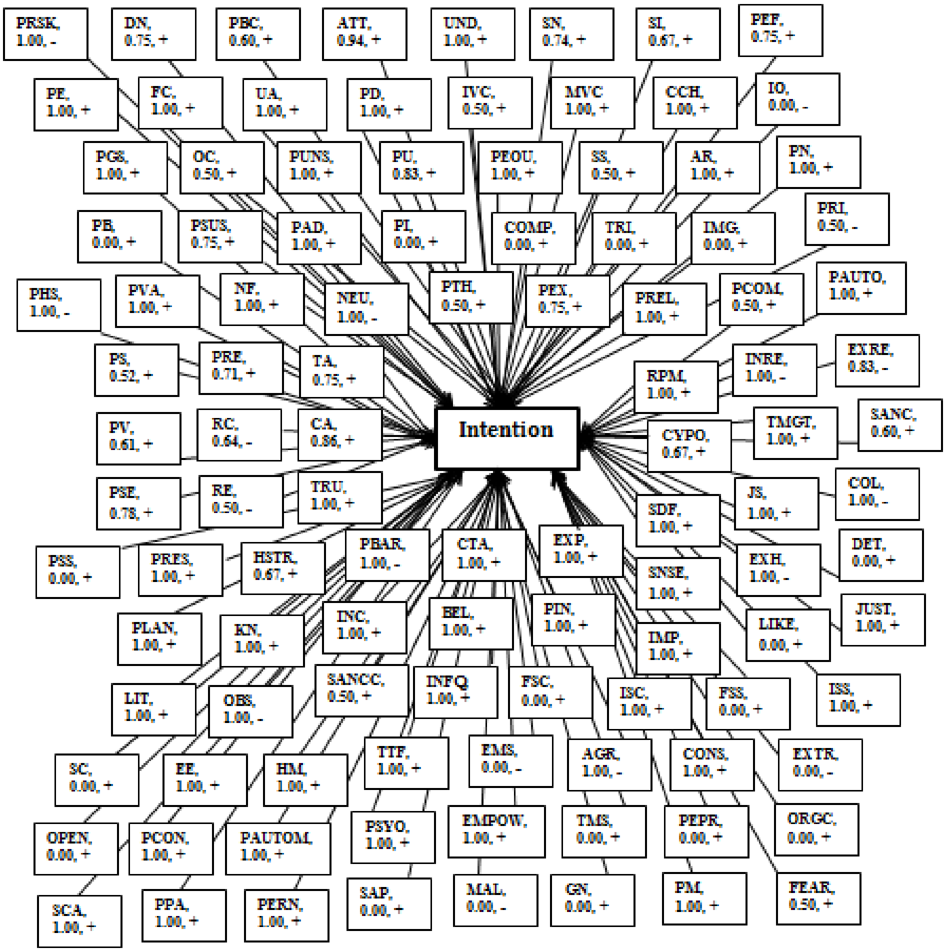

Fig. 6: Diagrammatic representation of all independent variables with intention

Furthermore, diagrammatic representation is meant to provide a visual representation of quantitative data to make it more detailed (Rayat, 2018). Furthermore, Rana et al. (2015) claim that this representation may be utilized to evaluate the weight-analysis of constructs in order to identify their overall findings. Indeed, all of the independent factors in such relationships are directly related to the focus variables, such as Intention, Behavior, and Protection motive. Therefore, all 138 papers were utilized to produce a diagrammatic depiction of significant and non-significant connections. As a result, all of the relationships are diagrammatically shown in this paper, together with their weight values and kind of association (positive or negative), in Figures 6, 7, 8, and 9, as Rana et al. (2015) did.

We discovered 108 variables that had direct correlations with the Intention. The number of BP, WU, PRO, and EXP among these variables was 4, 19, 56, and 89, respectively. Figure 6 also depicts a diagrammatic representation of all independent factors that have a direct relationship with intention.

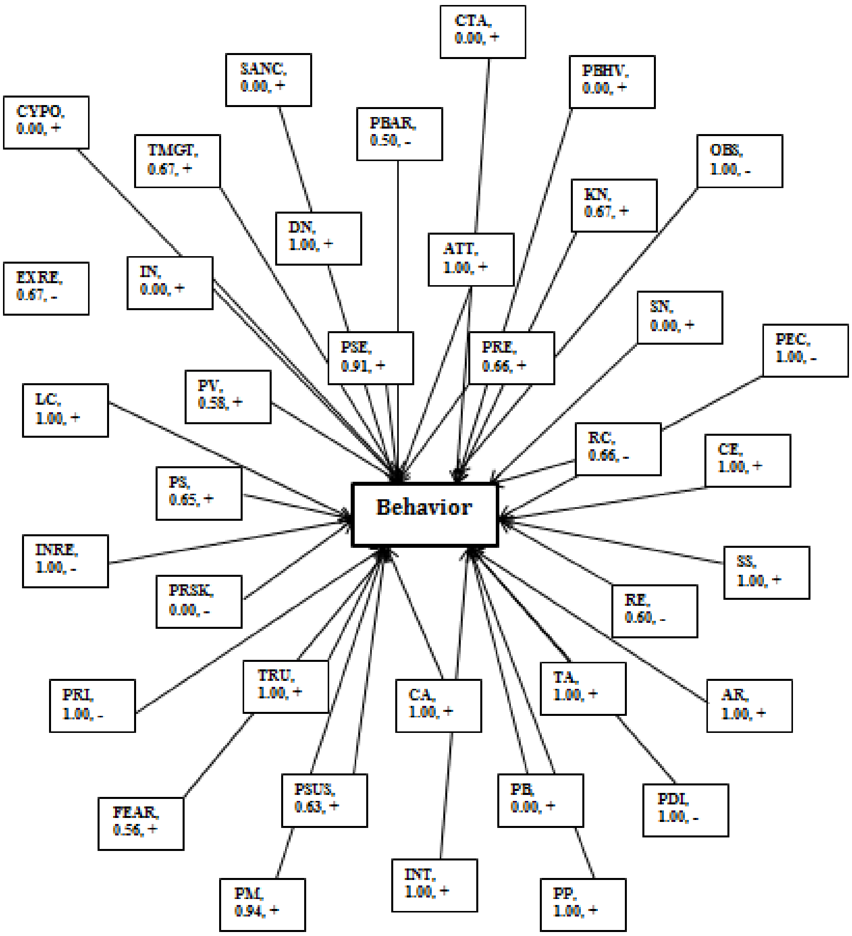

Fig. 7: Diagrammatic representation of all independent variables with behavior

We discovered 37 variables that had direct correlations with Behavior. Besides, the number of BP, WU, PRO, and EXP among these variables was 3, 10, 15, and 27, respectively. Fig. 7 also depicts a diagrammatic representation of all independent factors that have a direct relationship with Behavior. Furthermore, we discovered a total of 21 variables that had direct correlations with Protection Motivation. Here, the number of BP, WU, PRO, and EXP among these variables was 3, 9, 6, and 12, respectively. Figure 8 also shows a diagrammatic representation of all independent factors that have a direct relationship with Protection Motivation. Finally, we discovered a total of 18 factors that had direct correlations with Attitude. Here, the number of BP, WU, PRO, and EXP among these variables was 2, 4, 13, and 14, respectively. Figure 9 also depicts a diagrammatic representation of all independent factors that have a direct link with Attitude.

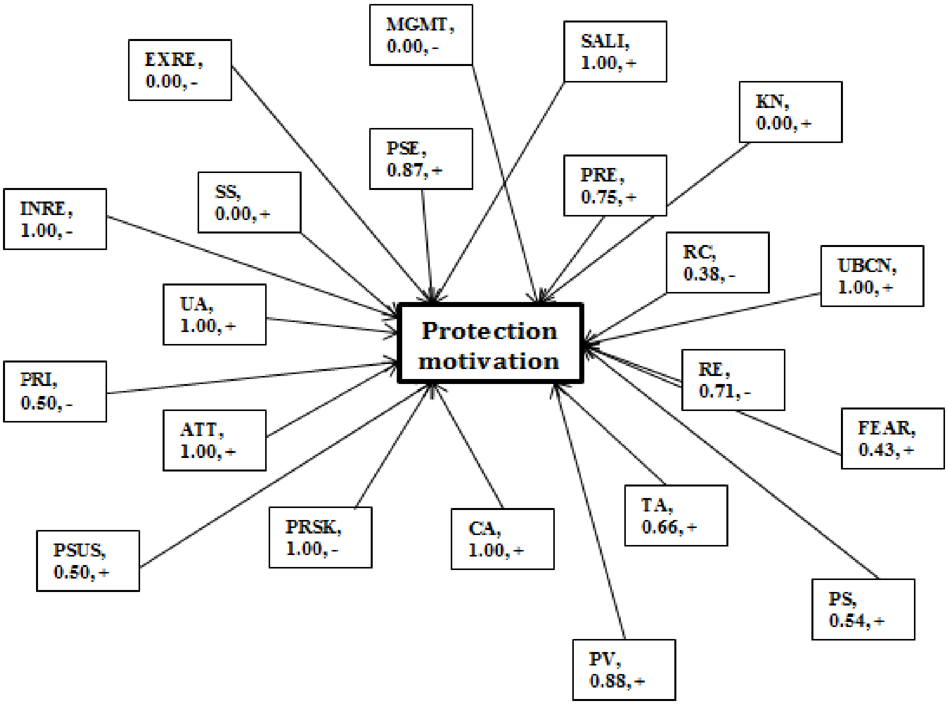

Fig. 8: Diagrammatic representation of all independent variables with Protection Motivation

Now, we can compare the weight value of Threat appraisal and Coping appraisal variables for different dependent variables named Intention, Behavior, Protection motivation, and Attitude. Notably, Severity, Vulnerability is part of Threat appraisal whereas Self-efficacy, Response efficacy, and Response cost comprises Coping appraisal.

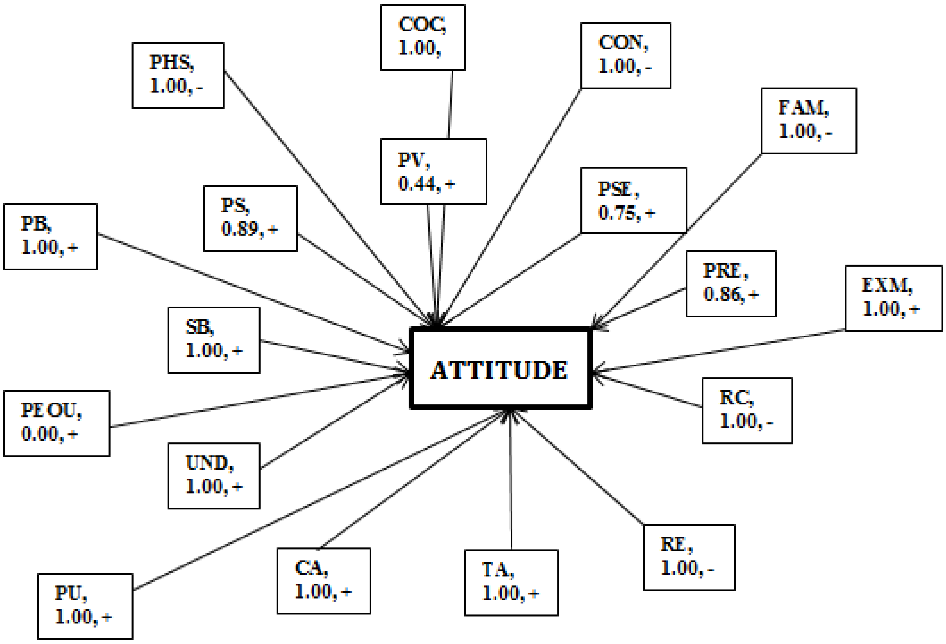

Fig. 9: Diagrammatic representation of all independent variables with Attitude

Table 5: Weight value comparison between threat and coping appraisal variables

Intention				Behavior				Protection motivation				Attitude			
Threat		Coping		Threat		Coping		Threat		Coping		Threat		Coping	
PS	0.52	PSE	0.78	PS	0.65	PSE	0.91	PS	0.54	PSE	0.87	PS	0.89	PSE	0.75
PV	0.61	PRE	0.71	PV	0.58	PRE	0.66	PV	0.88	PRE	0.75	PV	0.44	PRE	0.86
		RC	0.64			RC	0.76			RC	0.38			RC	1.00
AVE	0.56	AVE	0.71	AVE	0.61	AVE	0.77	AVE	0.71	AVE	0.66	AVE	0.66	AVE	0.87

It can be found from Table 5 that the average performance of the coping appraisal variables is better than the Threat appraisal variables in terms of weight values.

4.1. Inclusion of moderator in PMT

In this study, we are going to propose including the moderator/s with PMT for three reasons. To begin, the PMT's average predictive variance (R^2) was not determined to be sufficient in this investigation. The average variance of Intention, Protection motivation, and Behavior was 0.468, 0.473, and 0.421, respectively, which is less than moderate (0.5) (Hair et al., 2014). On the other hand, the moderating effect can increase the R^2 from 14.4% to 18% (Orpen, 1996), 65.4% to 78.4% (Saeidi et al., 2019), and 56.29% to 57.82% (Muli et al., 2017).

Second, most regular PMT constructs were found to be poor predictors of Intentions (except Coping appraisal), Behavior (except Perceived self-efficacy), Protection motivation (except Perceived vulnerability, Perceived self-efficacy, and Coping appraisal), and Attitude (except Perceived severity and Response efficacy). Furthermore, the weight values for Perceived vulnerability, Perceived severity, Perceived self-efficacy, Perceived response efficacy, and Response cost toward Intention were 0.52, 0.61, 0.78, 0.71, and 0.64, respectively, which is insufficient. Fortunately, in the case of Behavior, Protection, motivation, and Attitude, this weight value improved slightly. However, the overall result is still not satisfactory. According to Dang et al. (2019), one potential explanation for the inconsistent findings in prior research could be because these studies did not use a moderator.

Finally, the influence of moderators on the PMT has received less attention (Plotnikoff et al., 2009). Only four of the 138 articles utilized the five moderators. Gender, Personal health status, Personal health value, Uncertainty avoidance, and IT vision conflict were the moderators. Furthermore, (Guo et al., 2015) argue that the inclusion of moderators with PMT is justified.

5. Discussion

This research was carried out with three goals in mind. The first goal of this study was to investigate the use and expansion of PMT at the individual level for generic behavior over the last 7 years. Our first goal was evaluated using the following criteria, which are stated below:

- In recent years, there has been a constant increase in the number of publications. Furthermore, with the current excitement and the 27 papers released by mid-September 2020, it is projected that the number of publications in future years would skyrocket.
- Only five types of PMT applications are available. However, among these five applications, information security, health, and environmental concerns are highly preferred.
- In terms of applications, the United States (29 papers), Iran (16 papers), and China (7 papers) are the top contributors to information security, health, and the environment, in that order.

The second goal of this study was to identify the factors that aid in the development and extension of this theory. To achieve our second goal, we counted the frequency of each independent variable. Perceived severity, Perceived vulnerability, Perceived self-efficacy, Perceived response efficacy, and Response cost were the most commonly used PMT constructs. However, only 14.96% of variables were encountered enough times (5 times or more), while 86 (out of 147) variables were utilized only once. Aside from the regular constructs of PMT, the most frequent variables were Attitude (23 times) and Subjective norm (23 times), and many authors relied on these two variables to establish conceptual models in different domains.

The final goal of this study was to perform a weight analysis of the independent factors pertaining to Protection motivation, Intention, and Behavior. Notably, we included Attitude for weight assessment because it has been used in various papers as a mediator of Intention, Protection motivation, and Behavior. We have discovered four significant findings based on our weight analysis:

- Threat appraisal variables have greater weight values than coping-appraisal variables.
- The most powerful predictor of PMT is perceived self-efficacy.
- The weight values for the Attitude and Subjective norm are satisfactory.
- The majority of PMT's regular constructions are insufficiently consistent.

6. Conclusion

In the last 7 years, 138 quantitative methods, full-length, empirically tested, individual-level papers have been discovered only in journals and conferences resulting from 5 databases. Furthermore, this investigation discovered a previously unheard-of increase in the number of journals suggesting the theory's consumption stability and potential. This growth can be attributed to the increased availability and use of PMT in recent years, which has likely contributed to an increase in researchers' interest. However, some flaws and loopholes must be resolved before this theory can be properly used. This theory, for example, is primarily used to handle problems relating to health, information security, and environmental behavior. As a result, the application of this theory is extremely limited, and researchers need to seek out further applications. Most significant of all, in the immediate future a lot of further improvement is expected if the existing growth trend persists. Furthermore, the addition of two variables, Attitude, and Subjective norms, as well as moderators, is intended to assist the theory to handle a broader range of applications with greater predictive accuracy.

6.1. Theoretical and practical contribution

For prospective scholars, the present analysis provides many theoretical lenses which are almost new. It functions on the one hand as a guide to studies focused on PMT for generic behavior. It also includes research on the existence of variables in such studies, on the other hand. As a result, we have contributed to the existing literature in a way that was almost unknown in earlier investigations. First, this study investigated the utilization and growth of PMT from the perspectives of publications during the period 2014-2020, types of addressed applications, and involvement of various nations. Second, we counted the number of variables that contributed to the development and expansion of the PMT in various domains. Third, the depiction of a combined diagrammatic representation for analyzing the weight analysis contributes to the study's efficacy. Fourth, we performed a weight analysis to determine the significance of the predictor factors. To illustrate, several promising predictors, as well as best predictors, were identified that can influence Intention (56 promising predictors), Behavior (15 promising predictors), Protection motivation (6 promising predictors), and Attitude (13 promising predictors). These intriguing predictors have the potential to be the best forecasters, but they have not yet been fully examined. Jeyaraj et al. (2006) advised researchers to continue employing the best predictors and studying promising predictors inside their conceptual models for individual adoption-related studies. Finally, this study discovered the reasons for employing moderators with PMT. Therefore, suitable moderators are suggested for use in our studies with PMT. As a result, these contributions have filled research gaps for academics, allowing them to supplement current data with new knowledge. Furthermore, by employing this knowledge, the research community can be better educated, and researchers can be more encouraged to conduct further studies.

From a practical sense, the PMT is a component of the social marketing approach. As a result, this concept might be utilized to develop goods, services, and communications that suit people's needs. In addition to the conventional benefits, as a component of social marketing, this method can encourage favorable behavioral changes in individuals. In contrast, nonprofit organizations, charity foundations, government agencies, and public departments, for example, rely significantly on social marketing to raise public awareness (Cismaru et al., 2008). Besides, the recent rise in PMT among individuals, as well as the weight analysis results of the predictor elements, may affect enterprises, governments, and entrepreneurs in formulating business plans. Furthermore, individual users are continually presented with a slew of security hazards in their surroundings. While efficient solutions are frequently available, the motivation of end-users to engage in secure behaviors varies. Indeed, end-users are far less likely to engage in those actions if they are not appropriately motivated. Taking into account end users' motives for completing secure behaviors might result in procedures that drive higher adoption of security solutions and generate a safer environment in general. Therefore, our study opens up new and novel avenues for future threat-related research by distinguishing end users' various degrees of internalized encouragement.

6.2. Limitations and future works

There are some flaws in this analysis. To begin, data collection was restricted to only five databases as stated previously. Databases such as Proquest, Ebsco, ACM, Pubmed, Jstor, Hindawi, Wiley, and others, on the other hand, could be a source of information. Second, the search terms utilized in this weight analysis may be insufficient. Some more phrases like "information security model", "health model", "environmental model" etc. could also be used. Therefore, we may have missed some crucial articles and information as a result of the aforementioned factors. Finally, we discovered a prediction variance that applies to all types of applications. Variance (R^2), on the other hand, can be examined for each type of application, which can aid in selecting a more accurate moderator for each PMT application.

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