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The Relationship between Risk Perception and Risk Definition and Risk-Addressing Behaviour during the Early COVID-19 Stages

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Abstract: The purpose of this article is to show the effect of Risk Perception RP and Risk Definition RD on the Risk-Addressing Behaviour RB. To carry out this study secondary data was used from a semi-structured survey administered between February and June 2020, a period during the early stages of the COVID-19 pandemic. The study identified six dimensions of risk perception and thus tested six structural models. Risk perception (ξ, RP) is defined as an external latent variable in the study. It is also assumed that the risk perception variable may affect the risk definition variable (η RD). The application software SmartPLS was used to analyse data through exploratory factor analysis and partial least squares structural equation modelling on our research model. To achieve Convergent validity of the structural equation model of partial least squares, three criteria were met. In the study, Discriminant Validity was examined using the Fornell-Larcker criterion and Heterotrain-Monotrait Ratio (HTMT) coefficients. Results reveal that there is no direct relationship between the RB and "religion and beliefs", the "fear level, the experience", the "peer influences level" and the "openness". However, we found a positive relationship between the agreement on "knowledge" and on RB and statistically significant relationships between the agreement on the RD and the agreement on the "religion and beliefs", the "fear level", the "experience", the "knowledge", the "peer influences level" and the RB. Moreover, there is an indirect relationship when controlling for the agreement on the RD between the agreement on the RB and the agreement on the "fear level", the "experience", the "knowledge" and the "peer influences level". However, there is no relationship between the agreement on the "openness" and the agreement on the RB and a statistically significant but moderate relationship between the agreement on the RD and the agreement on the RB. Although, there seems to be abundant research on RP, so far we have found only a few studies on the influencing factors of RP, as effected by RB and RD, especially in distressed times such as during this current pandemic period of COVID-19. This study adds to body of literature and sheds new light on the interaction between RP, RB and RD in a time of distress. It provides important and original information that may be useful for government agencies, businesses, individuals, and the media when setting policies, governance structures, regulations, procedures and determining how to communicate.

Keywords: risk-addressing behaviour; risk perception; risk definition; structural equation modelling; risk management; sustainability

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1. Introduction

Different generations have defined the environment around us by the way they faced and responded to uncertainty. Disruptions to expectations have created the need to do something, i.e., to make decisions based on experience and knowledge and to challenge the 'status quo'. This, in a nutshell, defines humanity and life, and the concept of 'risk' and 'risk management'. How do people perceive risk and how do they define it? Does this influence the way they behave and deal with risk?

Therefore, our aim with this study was to investigate the influence of Risk Perception RP and Risk Definition RD on the Risk-Addressing Behaviour RB of individuals; which in the context of this study is defined as the manner in which individuals approach and manage the perceived risk, i.e., Risk Management. We show that a direct relationship exists between the RB and "religion and beliefs", the "fear level, the experience", the knowledge", the "peer influences level" and the "openness"; between the RD and "religion and beliefs", the "fear level", the "experience", the "knowledge"; the "peer influences level" and RB; an indirect relationship when controlling for the RD between the RB and the "fear level", the "experience", the "knowledge "and the "peer influences level" and a statistically significant but moderate relationship between the RD and RB. Moreover, a positive relationship was found between "knowledge" and RB. This information is important for understanding how the public evaluates and defines risk, how they behave toward risk, and what factors influence their RP in order to make effective decisions, predict public reactions to risk, and communicate risk in uncertain times, when a solution is not yet expected or known. The knowledge presented in this paper could influence the public and private sector's approach towards governance, policy making, regulation, procedures and communication. It provides important and original information that may be useful for government agencies, businesses, individuals, and the media when setting policies, regulations and procedures. Consequently, this study adds to body of literature and sheds new light on the interaction between RP, RB and RD in a time of distress.

Risk has different meanings for different people (Slovic 1987). Sjöberg (2000) states that we gain an understanding of risk through cultural, social evaluations and structured conceptions of the world. This has played a major role in the definition and development of the word 'risk'. The word risk first entered the English language in the 16th century and evolved from the French word 'risque' into 'Le Nouveau Petit Robert' (Rey-Debove and Lebeau-Bensa 1993). Translating the word 'risque' with the Latin word 'rescare', which means "to cut", it takes on a negative connotation (Grima and Bezzina 2018). Moreover, PRIMO (2020) highlight that this Latin definition also means 'to run into danger', which reflects the negative sentiments expressed in Grima and Bezzina (2018).

In ancient Greek, the word 'risk' is translated 'rhizikon', which comes from the word 'rhiza', meaning 'root'. However, the Arabic and Maltese language meaning of the word 'risk', which is translated as 'risq', is more positive and gives the word the religious meaning of God ('Allah' and 'Alla' respectively) granting prosperity to a person (Grima and Bezzina 2018).

Rohrmann (2008) notes that risk is often defined as the likelihood of harm or damage and that it is important to distinguish between psychological and physical phenomena and to know the difference between people's attitudes, behaviours and judgements when confronted with disturbances to the norm. He also emphasises that risk is a multifaceted concept that is not always negative but can also be positive or neutral, such as the adrenaline rush that results from an important event with an uncertain outcome.

People face risks on a daily basis. Some risks may pose a threat to an individual or society, some risks we underestimate and others we overestimate (Gaissmaier and Bodemer 2015). According to Jaeger et al. (2001, p. 16), risk is "a situation or event in which something of human value is at stake and the outcome is uncertain." Solomon Michael and Schopler (1982) defined risk as "the probability of an event occurring together with its consequences". Klinke and Renn (2002, p. 1071) echo this by noting that risk is "the possibility that human actions or events will lead to consequences that damage aspects of things that people value." This means that the severity of the event depends on the relationship between the action and the consequences. By mitigating the effects of changing the triggering event, the consequences can change. This means that an individual can judge the outcome as something desirable or undesirable and take action by accepting, controlling, reducing or even avoiding the risk. Therefore, the perception and definition of risk is a combination of the drivers, stimuli, triggers, consequences and causes. Hillson (2019, p. 2) defines risk as "uncertainty that matters". This means that risk matters because it affects our goals.

Other authors such as Vlek and Stallen (1980), Zuckerman (1979), Serin and Kuriychuk (1994) and Yates (1990), have seen the meaning of risk in a negative light, as the chance or probability of losses or seeking a reward or pleasure without boundaries or controls. On the other hand, Sjöberg (2000, p. 1) defines risk perception as "a phenomenon in search of an explanation." Behaviour is influenced by emotional, social and cognitive factors (e.g., decision-making). Chionis and Karanikas (2018) explain that many factors influence risk perception including personality, experience, beliefs, age, gender, education level, knowledge, culture and psychological context. One's social and individual characteristics can influence the way we think and react towards risk and forms one's risk perception (Schmidt 2004).

However, because risks are complex, it is important to know the strength of the inferred risk message in order to understand people's beliefs about their behaviour and decisions regarding risks to ensure that policymakers whose focus is on sustainability are aligned on all facets of risk perception (Weinstein and Lyon 1999). Experts often distinguish between 'objective' and 'subjective' risk. 'Objective' risk refers to the product of scientific research, especially health statistics, experimental studies, epidemiological investigations, and probabilistic risk analyses. 'Subjective' risk refers to the lay perception of this research, embellished by other considerations important to the public. This distinction is controversial because it characterises both the public and the experts (Fischhoff et al. 1984).

Risk perception is the subjective judgement that people form about the characteristics, severity, and ways of dealing with risks. One of the key elements is the sense of outrage and indignation that a risk evokes, which multiplies anxiety and runs quickly through society. The elements of voluntariness, knowledge, visibility and trust that increase or decrease fear and risk perception were explored in detail in a study by Cori et al. (2020) on risk perception and COVID-19. Our blind spot as a 'risk society' is our inability to recognise that definitions of risk are communicative assertions that have inherent power (Beck 1992). This is even more so when dealing with situations that involve crisis, such as pandemics, emergency responses or crisis situations that shake the balance of a system and create an overload of sudden demands (Dalli Gonzi 2019; Dalli Gonzi et al. 2019).

Looking further at the case of outbreaks, pandemic preparedness (as in the case of COVID-19) is a major concern for public health officials and leaders. In response to building and thinking about resilience, scientists and practitioners have developed scenarios and scenario tests that are an essential part of any ecosystem. This suggests that there should be sufficient scientific evidence to justify conclusions about the complexity and predictability of this risk. A pandemic puts the entire population at risk, including those who are not infected. It causes widespread disruption of normal lifestyles and work environments, leading to further stress that results in anxiety, illness and death due to cascading effects (Grima et al. 2020b). The evolution of research as the pandemic grows plays an important role in the definition and evolution of the word 'risk'. We will understand much more in the coming months than what was known in the early stages of the pandemic COVID-19.

2. Risk-Addressing Behaviour RB

Human development is about human behaviour, which in turn is about managing risk (Byrnes et al. 1999; Kasperson 2012). Beyth-Marom et al. (1993) point out that RB is about taking an action that involves the possibility of loss. Several studies emphasise that RB differs across countries, time and individuals, and that risk-taking varies across the life course even among the same individuals (Ayton et al. 2020). Trimpop (1994, p. 9) proposes that RB is "any consciously or unconsciously directed behaviour with a perceived uncertainty about its outcome and/or about its potential benefits or costs to the physical, economic, or psychosocial well-being of self or others." Galizzi and Tempesti (2015) explain that an individual may participate in risky behaviour primarily because they are unaware of the consequences and/or because they are tolerant of risk. Furby and Beyth-Marom (1992) and Byrnes et al. (1999) pick up on the former reason by claiming that RB occurs because the person taking the risk has no idea of the negative outcomes.

RB depends on the control one has over the risk. When individuals feel vulnerable and have exhausted all options, they take risks whatever the outcome (Zinn 2008). According to Weber et al. (2002), engaging in risky behaviour happens since they believe that their behaviour is not too risky, or they believe that it can lead to benefits. However, individuals react differently to uncertain information and the way they act to make decisions is based on their personality characteristics, experiences and tolerance to uncertainty (Waters Sara et al. 2014).

How individuals behave in reaction to a risk exposure depends on whether one understands the nature of the risk, how exposed s/he is to the risk and the steps available to mitigate that risk (Rohrmann 2008). Risk management is the appetite of society and their judgement on whether the risk is acceptable or not and the decisions taken to adequately add controls (Klinke and Renn 2002). This depends on various factors, namely the analysis made, the timing, the environment, their logistical interpretation, deliberation and quantification. In addition, one must not forget that risk is a feeling, therefore one intuitive and instinctive reactions should be taken into consideration. One's intuition, instinct and gut feeling helps to deal with uncertainties. However, as life became more complex, individuals adopted analytic and logical ways of reacting to uncertainties (Slovic 2014).

Slovic (2010) suggests further that the best way to manage risk is to understand how individuals think and feel about uncertainties and to recognise behaviours and attitudes, which are determined by the need for sustainability, specifically the environment, social, psychological, political, economic, regulatory and cultural forces. Understanding an individual's cognitive process will help researchers determine how individuals and societies can improve their RP and decrease the noise that dampens their risk judgment. Compared to other risk areas, such as environmental risks, far less is known about how the public perceives risks associated with emerging infectious diseases (de Zwart et al. 2007), while most of the evidence on risk perception comes from studies during previous pandemics (Dryhurst et al. 2020). Although there are several studies that point to factor variables that are important in addressing and measuring a country's vulnerability, the COVID-19 pandemic also highlighted a serious need to target areas or functions that may have been overlooked and to develop tools that are flexible enough to help national risk managers and policy makers proactively identify and determine their country's risk vulnerability. Measuring a country's vulnerability is important to determine when action needs to be taken or to flag the problem based on existing tolerance thresholds (Grima et al. 2020a).

Understanding how the public behaves is critical for the government to develop effective communication strategies and ensure high compliance with protective behaviours (Ning et al. 2020). Technological advances and their impact on humanity have led to increased risk awareness, and objective, statistical assessments are often insufficient to reduce the public's fears and anxieties. Research on risk perception using psychological and sociological approaches has attempted to fill this gap (Renn and Swaton 1984). For example, in studies addressing adolescent risk behaviours (Bozzini et al. 2020), through an exclusive selection of longitudinal studies, the authors were able to examine factors that predict adolescent risk behaviours and thus justify the creation of public policies to prevent risk behaviours in a way that can support the health sector. Another study by Reniers et al. (2016) examined influences on adolescent risk behaviours and provided insights for targeted prevention and intervention efforts as research noted the increase during adolescence to the association of increased reactivity to emotions and immature capacity for self-regulation. Understanding risk behaviours can help public health agencies make better decisions and provide public procedures and recommendations. Also, in terms of dealing with the pandemic COVID-19, improving risk perception and increasing preventive behaviours can help health workers evolve in terms of understanding current guidelines and protecting themselves and others from infection, which will help contain the spread of disease, while strongly suggesting that governments publish guidelines based on practices that will be modified as the pandemic progresses (Arslanca et al. 2021).

3. Aim

As noted in the introduction the aim of this study is to investigate and determine the influence that RP and RD have on the RB of individuals. Moreover, as we note from the literature, RB is a multidisciplinary concept that may have different meanings in different domains. In this study, we examine people's risk perception to find out whether it plays a role in individuals' behaviour. Since most studies on risk perception were conducted in the 1980s, 1990s, and 2000s, it was important to conduct a current study on risk perception based on the current risks that people experience. Risks are constantly changing, so new risks are constantly emerging that can influence people and society's views and actions to address those risks.

4. Research Methodology

To carry out this study we used the secondary data extracted from part of the data of the structured portion of the survey designed and carried out by two of the authors for a previously unpublished study by (Girlando 2020) and a later published chapter by Girlando et al. (2021). This survey had been administered, using a non-probability purposive and snowballing sampling, to participants who were reached on social media, telephone, by email or other communication systems such as Skype, Zoom, Goto, Ms Teams, WhatsApp, Signal and Hangout, between February and June 2020. Non- probability purposive sampling since not all members of the population had an equal chance of participating in the study and the population was at first restricted to friends of the authors. Moreover, to increase the number of participants we asked our friends to extend the invite to their friends, hence the non-probability snowballing sampling. Participants were treated with full confidentiality and anonymity.

A total of 466 valid responses were received. The majority of the participants were females (67.20%) when compared to males (32.8%). Most of these participants were of an age between 16 and 25 (31.5%); 26–35 (25.5%), 36–45 (12%), 46–55 (9.7%) and 56–65 (12.2%), respectively, with the 65+ age group accounting for 9.0%, contributing least toward this study. This may be an indication that they might not be familiar with the systems being used.

Also, the majority of the respondents were single, accounting for (51.9%), when compared to married respondents, accounting for (37.3%). Most participants had a bachelor's degree (33.7%) and a postgraduate degree (31.5%). Moreover, most respondents live in Central Europe (52.8%) with the rest were from Southern Europe (12.2%) and Northern Europe (35%).

The summary statistics of responses on RD, RB and RP have been tabled as Table A1 in the Appendix A. Using an online sample size calculator designed by Creative Research Systems (n.d.), it was determined at 95% confidence level and a confidence interval of 5 that for an unknown population a total sample of 384 participants would be required for the sample to be representative. Moreover, Deb and Lomo-David (2014) suggest that in their view an adequate participant rate per variable is between 1:4 and 1:10. Meaning that the representative sample for our 32 variables would need to be between 128 and 320. Based on the statistical calculation and this rule of thumb we can consider our sample as representative. However, since we used digital means and had no control of the respondents, the findings are based on the sample responses.

It is pertinent to note that the period chosen for this survey was a period of uncertainty, that is, during the early stages of the COVID-19 pandemic when the world was still unaware of any vaccine or medicines to combat this infectious and deadly virus.

The chosen RD, RP and RB statements for this study were determined by Girlando (2020), from the preliminary interviews she carried out before designing the survey.

The part of the questionnaire data used consisted of the following sections:

- An Introduction: Information about the study.
- Section 1: Question relating to participant's gender, age, marital status, education level and region.
- Section 2: RD statements (RD1 to RD6) (Girlando 2020).
    - ➢ RD1-Risk is the possibility that something unwelcome or unpleasant will happen
    - ➢ RD2- Risk is the threat of a negative occurrence/damage
    - ➢ RD3-Risk can be an opportunity for positive outcomes
    - ➢ RD4-The risk makes me feel vulnerable
    - ➢ RD5-Risk is weighing the pros and cons
    - ➢ RD6-Risk is the chance of loss or possibility
- Section 3: RB statements (RB1 to RB3) (Girlando 2020).
    - ➢ RB1-Try to reduce the risk if you do not understand it
    - ➢ RB2-Develop a portfolio of options
    - ➢ RB3-Evaluate the risk and then decide on what to do
- Section 4: RP experiences statements (RP1 to RP23) (Vide Table 1).

A 5-point Likert scale was used to measure the attitudes, views and behaviours of the respondents towards the statements on RP, RB and RD '1′—strongly agreeing and '5′ strongly disagree with the statements provided in the questionnaire. The higher the score value of the RD means that the participant agrees on the way they define/identify risk and vice versa. The higher the scoring given to the RB by the participants means that they agree on the way they address and behave in the face of risk and vice versa. Similarly, the higher agreed RP scores indicate that they agree on the way they perceive risk.

5. Data Analysis

The variable scale used in this study consisted of a total of 32 items, summary statistics of which are shown in Appendix A. RD and RB consist of six and three items, respectively, but RP consists of multiple factors. Exploratory Factor Analysis (EFA) was used to determine the RP factor structure and to examine its internal reliability. It is a technique that is used to reduce a large number of variables (in this case 23 RP variables) into fewer numbers of factors. This technique extracts maximum common variance from all variables and puts them into a common score, as an index of all variables, which we can use for further analysis. Principal Component Analysis as the extraction method and Varimax as the rotation method was preferred. As a result of the EFA, six factors with eigenvalues greater than one were found. It was found that the factors explain 53.359% of the total variance. Sample adequacy was examined according to the KMO measure and it was found that the number of samples was sufficient. Whether the correlation matrix used in obtaining factor loadings is unit matrix was tested by using Bartlett's Test of Sphericity approach and Bartlett's Test statistics were found to be significant. Therefore, it was decided that the data matrix was suitable for factor analysis. The results of the EFA are given in Table 1 (Hair et al. 1998).

Table 2 shows the statements that are grouped under each of the six factors. The terms given to each Factor Dimension was determined using the thematic analysis as suggested by Braun and Clarke (2006) on the items under each of the six Factor Dimensions. Factor 1 was termed "Religion" explained 11.08% of the variance and comprised of five items. Factor 2, termed "Fear", explained 10.95% of the total variance and comprised of four items. Factor 3, termed "Experience", explained 9.83% of the total variance and comprised of five items. Factor 4, termed "Knowledge", explained 7.69% of the total variance and comprised of four items. Factor 5, termed "Peer Influences", explained 7.03% of the total variance and comprised of three items. Factor 6, termed “Openness”, explained 6.77% of the total variance and comprised of three items (Hair et al. 2017).

Table 1. Exploratory Factor Analysis Results for the Risk Perception Scale.

Label	Items	Component					
		1	2	3	4	5	6
RP01	Risk is something created by society because I fear the same risk society fears	0.436					
RP02	Religion helps shape my world-views and influences the way I perceive and respond to risks	0.815					
RP03	When hazards occur, I turn to religion for reassurance	0.826					
RP04	I am attracted to beliefs that are in favour of my values and world-views and tend to ignore information that does not agree with my current beliefs	0.690					
RP05	My religion/values influence my attitudes, behaviour, lifestyle and decisions	0.732					
RP06	I tend to correct my behaviour to fit in the social norms and be accepted by society		0.546				
RP07	The more I search for information about a risk event, the more I perceive the risk as riskier and my levels of fear increase		0.609				
RP08	When coming across a risky situation I am less likely to take control and rely on others for decision-making		0.589				
RP09	When I experience fear, I feel Helpless and Thus, perceive the event as Riskier		0.667				
RP10	Accurate knowledge would reduce my fears and worries and reduce negative image about a risk event			0.570			
RP11	I gain knowledge about the environment from friends, family, school and the media and as a result, this knowledge influences my risk perception			0.497			
RP12	Any risk events that I experienced in my life had an effect on my current behaviours and attitudes towards those risks			0.704			
RP13	With my life experiences, I have learned how to deal with risks and tend to take more precautions			0.750			
RP14	Work experience helped me view risks differently				0.704		
RP15	Knowing that there are safety and control risk measures at my workplace affects my risk perception and makes me feel more at ease and satisfied to work in a safe environment and makes me feel more in control when coming across a risky event				0.716		
RP16	The more I know risks the more I feel I have more control over the risks and I am more likely to respond to an emergency.]				0.729		
RP17	Education helps me understand risks and be more knowledgeable on how to reduce the risk of injury, damage or death				0.731		

Table 1. *Cont.*

Label	Items	Component					
		1	2	3	4	5	6
RP18	When I was a teenager I felt influenced by peers to engage in risky behaviour (for example drugs, alcohol, smoking, new things, adventures, school, winning) to be accepted.					0.712	
RP19	As an adolescent, I did not feel vulnerable to risks and was more likely to take risks as I was not able to control my behaviour					0.786	
RP20	As a teenager, I underestimated the severity of risks and found it hard to avoid participating in risky activities					0.851	
RP21	As a person I am outgoing, seek excitement, new experiences, I am enthusiastic, adventurous, sociable and positive						0.716
RP22	As a person, I am hard-working, self-disciplined, punctual, organised and pursue my goals						0.640
RP23	As a person, I am open-minded, curious, open to new ideas and creative						0.622
	Eigenvalues	3.21	3.18	2.85	2.23	2.04	1.96
	% of Variance	11.08	10.95	9.83	7.69	7.03	6.77
	KMO and Bartlett's Test	0.808					
	Bartlett's Test of Sphericity	4017.78 P = 0.000					

Source: Authors' Compilation (Data and Framework adapted from (Girlando 2020)).

Table 2. Dimensions of Risk Perception RP and Items.

Religion and Beliefs	RP01, RP02, RP03, RP04, RP05
Fear	RP06, RP07, RP08, RP09
Experience	RP10, RP11, RP12, RP13
Knowledge	RP14, RP15, RP16, RP17
Peer Influences	RP18, RP19, RP20
Openness	RP21, RP22, RP23

Source: Authors' Compilation.

A scale of nine items was used to determine the dimensions of RD and RB, and common factor structures were determined using exploratory factor analysis. The results of exploratory factor analysis show that the scale can be summed up into two factors. The first factor with an eigenvalue of 2.894 and describing 32.16% of the total variance was termed Risk Definition (RD) and the second factor with eigenvalue calculated as 2.002, accounting for 22.24% of the total variance was termed risk-addressing behaviour (RB). The KMO measure of RD and RB dimensions was 0.861. The correlation matrix used to obtain factor loads was examined through Bartlett's Test and Bartlett's test statistic and was found to be statistically significant (Bartlett's Test Sphericity = 1087.87 P = 0.000). As with the RP scale, Principal Component Analysis and Rotation Method: Varimax were preferred in determining the common factor structure. Analysis results are shown in Table 3.

Table 3. Exploratory Factor Analysis Results for the RD and RB Scale.

Label	Items	Component	
		1	2
RD5	Risk is weighing the pros and cons	0.772	
RD2	Risk is the threat of a negative occurrence/damage	0.730	
RD6	Risk is the chance of loss or possibility	0.706	
RD3	Risk can be an opportunity for positive outcomes	0.699	
RD4	The risk makes me feel vulnerable	0.654	
RD1	Risk is the possibility that something unwelcome or unpleasant will happen	0.504	
RB1	Try to reduce the risk if you do not understand it		0.785
RB3	Evaluate the risk and then decide on what to do		0.779
RB2	Develop a portfolio of options		0.620
	Eigenvalues	2.89	2.002
	% of Variance	32.16	22.24
	KMO and Bartlett's Test	0.861	
	Bartlett's Test of Sphericity	1087.87 P = 0.000	

The model for determining the possible effect of individuals' risk perception and RP on RB in the research is as in Figure 1.

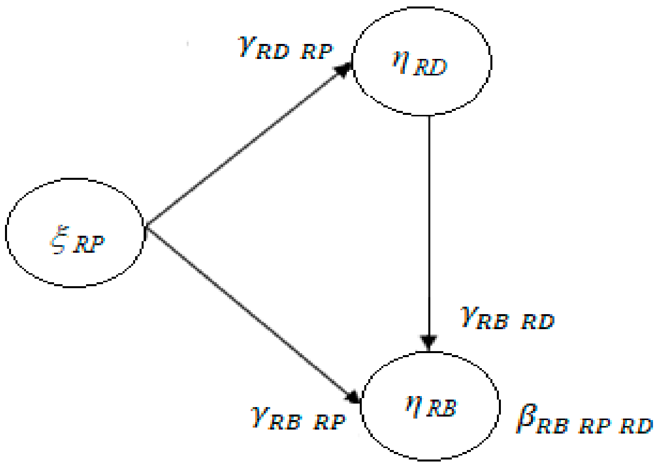

Figure 1. Research Model (Source: Authors' Compilation).

In the research, risk perception RP is exogenous, RB is an endogenous variable and RD is the mediation endogenous variable. In the model, $\gamma_{RD\ RP}$ shows the direct effect of individuals' risk perception. On the other hand, $\gamma_{RB\ RP}$ shows the direct effect of individuals' risk perception on the RB variable. Similarly, $\gamma_{RB\ RD}$ shows the direct effect of RD of individuals on RB. $\beta_{RB\ RP\ RD}$, shows the direct effect of RP and RD on RB.

Risk perception (ξ RP) is defined as an external latent variable in the study. It is also assumed that the risk perception variable may affect the risk definition variable (η RD). For this reason, RD is defined as the internal mediation latent variable. Based on this definition, indirect effects were also examined in the study. All dimensions obtained by the explanatory factor analysis of the risk perception, RD and RB scales in the tested models were put into the structural model and analysed. These research models have been tested using SmartPLS (PLS-SEM) software.

6. Partial Least Squares Structural Equation Modelling

We used SmartPLS software for our data analysis. The logic of this analysis is based on PLS-SEM, which is variance-based structural equation modelling. PLS-SEM analysis methods use the least-squares method, such as regression, as a prediction method. It is based on the estimation of relationship coefficients, which maximizes the R^2 value of the dependent variable and it is a method to minimize the variance of error terms

(Hair et al. 2014, pp. 174–77). As in the method of covariance-based structural equation modelling, when the model becomes more complex, the number of predicted parameters does not require larger sampling. In addition, the method does not require any distribution assumptions in structural equation modelling, it creates samples based on the bootstrap technique from the data set and it is a nonparametric method that deals with parameters obtained from each sample (Civelek 2018, pp. 109–15). To achieve Convergent validity of the structural equation model of partial least squares, three criteria must be met. First, the standard factor load of each observed variable belonging to hidden variables must be less than 0.90 and greater than 0.70 (Chin 1998, pp. 295–336). The second criteria for each structure (the Composite Reliability (CR) and Cronbach Alpha (CA)), convergent validity and discriminant validity must be ensured, and the values must be greater than 0.70 (Hair et al. 2017, pp. 111–122). Finally, the Average Variance Extracted (AVE) value for each structure must be higher than 0.50 (Fornell and Larcker 1981). It should also be CR > AVE (Gürbüz 2019, pp. 77–82) (Kline 2013).

In PLS-SEM, the predictive power of the model can be calculated by R^2, f^2, Q^2. The fact that the Q^2 value for endogenous variables is greater than zero shows that the research model has the power to predict endogenous variables. It shows that if the value of Q^2 is in the range of 0.02 to 0.14, there is less relationship between the variables than if it is between 0.15 and 0.34, and if it is between $Q^2 > 0.35$, there is a high estimation power, and the model estimates the original observed variables successfully. The R^2 value gives the explanation rate of exogenous variables on the endogenous variable. Another effect size is f^2. f^2 gives the endogenous variable explanation rate of exogenous variables. If the effect size is 0.02 and above, it shows a low effect, if it gets a value of 0.15 and above, it shows a medium effect, if it gets values of 0.35 and above, it shows a high effect (Hair et al. 2017).

7. Model Validity and Parameter Estimates

In the study, six dimensions of risk perception were determined according to the factor analysis results. Therefore, six structural models were tested. In the first model, the religion and beliefs dimension was taken as the external latent variable from the RP of the individuals in the test. In the model, the effects of individuals' religion and beliefs on RP and RB were examined. The hypotheses for the model are given below.

H_{R1}: As religion and beliefs increase in individuals, RD increases.
Meaning that the more importance the participants gave to religion and belief the more they agree on the way they define/identify risk.
H_{R2}: As religion and beliefs increase in individuals, RB also increases.
Meaning that the more importance the participants gave to religion and belief the more they agree on the way they address and behave in the face of risk.
H_{R3}: As RD increases in individuals, RB also increases.
Meaning that the more the participants agree on the way they define and identify risk the more they agree on the way they address and behave in the face of risk.

The first thing to do in structural equation model tests is to check the outer loadings. According to Hair et al. (2017), factor loads should be 0.708. However, if the factor load is between 0.40 and 0.70, the AVE (Average Variance Extracted) and CR (Composite Reliability) coefficients of the latent variable to which the indicators belong should be checked. If the AVE and CR values have reached the threshold values, these indicators are not removed from the model (Yildiz 2020, p. 66). Since AVE and CR threshold values were reached in the study, variables with a load below 0.70 were not excluded from the analysis. Internal consistency reliability of the latent variables was examined and it was determined that the Cronbach's Alpha and rho_A values in the RB variable were between 0.60 and 0.70. In other variables, it was determined to be above 0.80. Since the CR value was found to be higher than 0.80 for all three variables, it was understood that the reliability of the research variables was provided for internal consistency. Since AVE values obtained were above 0.50 for all three variables for the convergent validity, convergent validity was also provided. In the study, Discriminant Validity was examined using the Fornell-Larcker criterion and Heterotrain-Monotrait Ratio (HTMT) coefficients. According to the Fornell-Larcker criterion, values on the diagonal should be higher than the 0.70 threshold value. Fornell-Larcker criteria for the first model was found to be higher than 0.70 (Religion: 0.742; Risk Behaviour: 0.758; Risk Definition: 0.713) for all three variables (Table 4). Similarly, it was determined that the values calculated in the HTMT coefficients were less than the threshold value of 0.85 and the discriminant validity was ensured. Another measure of fit is the SRMR (Standardized root mean square residual) value which was calculated as 0.086 and the fit of the structural model was found to be poor. We also examined whether there is multicollinearity among the variables, and it was determined that the VIF values were less than 3 and the maximum value was 2.337. Therefore, it was decided that there was no multicollinearity among the observed variables. The results obtained are given in Table 4.

Table 4. Evaluation of Reflective Measurement Models and Structural Models for Model One.

		Religion	Risk Behaviour	Risk Definition
Religion		0.742		
Risk Behaviour		0.083	0.758	
Risk Definition		0.266	0.454	0.713
AVE		0.555	0.575	0.508
Rho_A		0.865	0.662	0.819
Cronbach's Alpha		0.808	0.636	0.802
Composite reliability (CR)		0.859	0.801	0.859
HTMT	Risk Behaviour	0.191	-----	
	Risk Definition	0.302	0.602	
SRMR		0.086		----
Predictive power Q^2			0.033	0.107
Adjusted R^2			0.202	0.064
VIF		Minimum	1.203	
		Maximum	2.337	

Source: Authors' Compilation.

The model, in which the religion and beliefs variable is an exogenous latent and the RD variable is the internal mediator latent variable, has been tested with the SmartPLS software. The results obtained are given in Figure 2, which shows the standard solution.

As shown in Figure 2

- We observe a positive ($\beta = 0.266$) and statistically significant (t = 7.129, P = 0.000) causal effect of religion and beliefs on the RD. According to this determined relationship, an increase in the participant's agreement to the statement religion and beliefs of individuals effects positively RD's agreement score. Hence. H_{R1} was supported.
- We observe a positive ($\beta = -0.041$) and statistically significant (t = 0.875, P = 0.381) causal effect of RB on the religion and belief in individuals. Therefore, H_{R2} could not be supported.
- We observe a positive ($\beta = 0.464$) and statistically significant (t = 8.520, P = 0.000) causal effect of the RD on the RB of individuals. So, an increase in the agreement on RD by participants affects positively the agreement on RB. Hence H_{R3} was supported.

When looking at the predictive power of the RB and the RD variables of the model in PLS-SEM, it was determined that the Q^2 value is between 0.02 and 0.14 and has a small level of predictive power. Looking at the R^2 values, it was determined that the religion and beliefs variable explained 6.9% of the RP variable and 20.4% of the RB variable. When looking at the f^2 values, it was determined that the religion and beliefs variable had no effect on explaining the RB ($f^2 = 0.002$), but had a small effect ($f^2 = 0.076$) in RD. It was determined that the RD variable has a moderate effect ($f^2 = 0.253$) on RB.

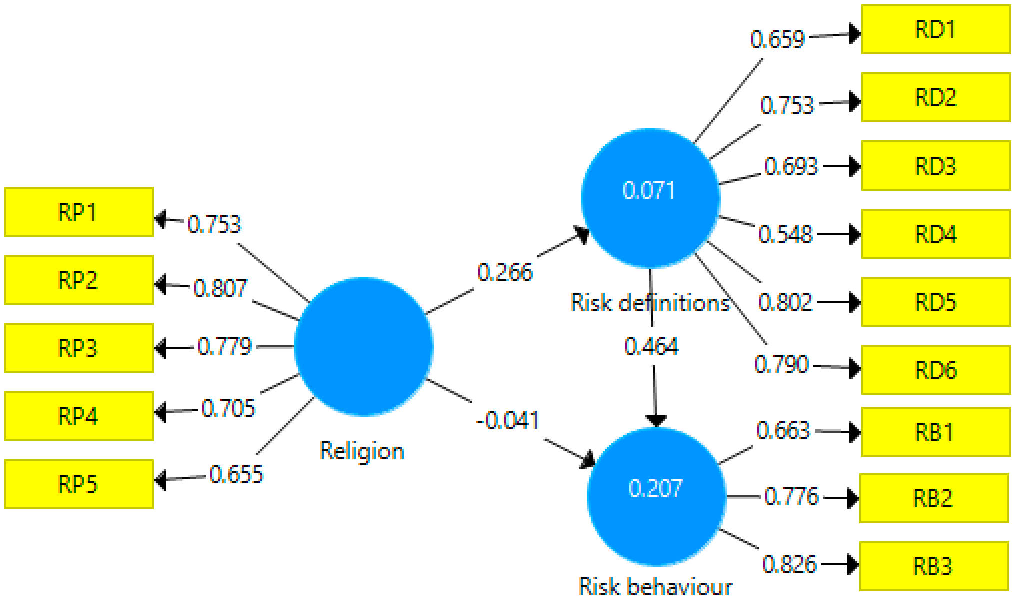

Figure 2. Model One Structural Path Graph (Source: Authors' Compilation).

The fear variable was taken as the exogenous variable in the second model tested in the study. The effect of the fear variable on RD and RB has been examined. It was determined that there are indicators with load values between 0.50–0.70 in factor loads in the model. These indicators were not excluded from the research model since the AVE values are higher than the 0.50 threshold.

In the second model, the internal consistency reliability of the latent variables was examined, and it was determined that the Cronbach's Alpha and rho_A values in the RB variable were lower than 0.70. Similarly, the Cronbach's Alpha in fear was calculated as less than 0.70. In other cases, it was determined to be above 0.80. Since the CR value was found to be 0.80 or higher for all three variables, it was understood that the internal consistency reliability of the research variables was provided. Since AVE values were obtained above 0.50 for all three variables for convergent validity, convergent validity was also provided.

Discriminant validity was also examined in the second model and it was determined that the Fornell-Larcker criterion and the HTMT coefficients met the criteria. According to the Fornell-Larcker criterion, values above the diagonal were determined to be higher than the 0.70 threshold value. Similarly, it was determined that the values calculated in HTMT coefficients were less than 0.85 and discriminant validity was ensured as another fit measure, the SRMR value was calculated as 0.079 and found appropriate. The maximum VIF values, for whether there is linearity between the variables, are determined as 1.813. Therefore, linearity was achieved between observed variables. The results obtained are given in Table 5.

The path graph for the second model tested is given in Figure 3. In Figure 3, the following hypotheses have been tested.

H_{F1}: As the fear level of individuals increase, the level of RD also increases.
Meaning that the more importance the participants gave to fear level the more they agree on the way they define/identify risk.
H_{F2}: As the level of fear increases, the RB also increases.
Meaning that the more importance the participants gave to fear level the more they agree on the way they address and behave in the face of risk.
H_{F3}: As the RD level of individuals increase, the level of RB also increases.
Meaning that the more the participants agree on the way they define and identify risk the more they agree on the way they address and behave in the face of risk.

Table 5. Evaluation of Reflective Measurement Models and Structural Models for Model Two.

		Fear	Risk Behaviour	Risk Definition
Fear		0.710		
Risk Behaviour		0.006	0.758	
Risk Definition		0.189	0.460	0.712
AVE		0.504	0.574	0.507
rho_A		0.714	0.664	0.823
Cronbach's Alpha		0.684	0.636	0.802
Composite reliability (CR)		0.800	0.800	0.858
HTMT	Risk Behaviour	0.160	-----	
	Risk Definition	0.238	0.602	----
SRMR		0.079		
Predictive Power Q^2			0.113	0.018
Adjusted R^2			0.215	0.034
VIF		Minimum	1.207	
		Maximum	1.813	

Source: Authors' Compilation.

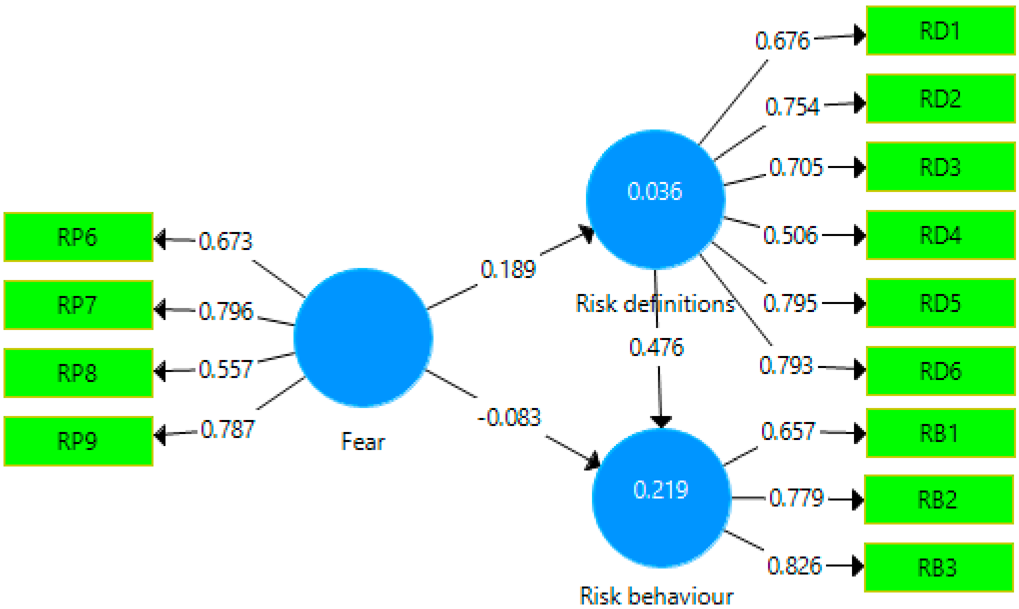

Figure 3. Model Two Structural Path Graph (Source: Authors' Compilation).

Figure 3 shows that:

- We observe a positive (β = 0.189) and statistically significant (t = 3.321, P = 0.001) causal effect of the fear level of individuals on the level of the RD. An increase in the participants' agreement on the fear level of individuals affects positively the participants' agreement on RD. Hence H_{F1} was supported.
- We observe a positive (β = −0.083) non- statistically significant (t = 1.262, P = 0.213) causal effect of the fear level of individuals on their RB level. H_{F2} could not be supported as this relationship was not statistically significant.
- We observe a positive (β = 0.476) and statistically significant (t = 9.573, P = 0.000) causal effect of the RD level of individuals on their RB. In this case, an increase in the participants' agreement on the RD level of individuals affects positively the participants' agreement on the RB. As with model one, H_{F3} is therefore supported in model two.

In the PLS-SEM model for the second model, it was determined that the predictive power of RB variables, Q^2, was between 0.02 and 0.14 and had a low level of predictive power. Looking at the R^2 values and the fear variable, it was determined that 3.17% of the RD variable and 18.1% of the RB variable were explained. Looking at the f^2 values, it was determined that the fear variable did not affect explaining the RB (f^2 = 0.009), and it was lowly effective in defining the risk (f^2 = 0.037).

In the third model tested in the study, the experience variable was taken as the exogenous variable. The effect of individuals' social experiences on RD and RB has been studied. It was determined that there are indicators with a load value below 0.70 in factor loads in the model. These indicators were not excluded from the research model since the AVE values were higher than the 0.50 threshold.

In the third model, the internal consistency reliability of the latent variables was examined, and it was determined that the Cronbach's Alpha and rho_A values of the RB and experience variables were between 0.60 and 0.70. Since the composite reliability (CR) value was found to be 0.80 or higher for all three variables, it was understood that the internal consistency reliability of the research variables was provided. For the convergent validity, in other words, the AVE (Average Variance Extracted) values for all three variables were obtained above 0.50, so the convergent validity was provided. The discriminant validity for the third model was also examined and it was determined that the Fornell-Larcker criterion and the HTMT coefficients met the criteria (>0.70). Similarly, it was determined that the values calculated in HTMT coefficients were less than 0.85 and the discriminant validity was ensured. SRMR value, which is another measure of fit, was calculated as 0.080 and found appropriate. In the model, the maximum VIF value was calculated as 1.813, and there was no multicollinearity between variables. Obtained results have been shown in Table 6.

Table 6. Evaluation of Reflective Measurement Models and Structural Models for Model Three.

		Experience	Risk Behaviour	Risk Definition
Experience		0.720		
Risk Behaviour		0.116	0.759	
Risk Definition		0.175	0.459	0.712
AVE		0.519	0.577	0.506
Rho_A		0.694	0.654	0.826
Cronbach's Alpha		0.695	0.636	0.802
Composite reliability (CR)		0.812	0.802	0.858
HTMT	Risk Behaviour	0.175	-----	
	Risk Definition	0.233	0.602	----
SRMR		0.080		
Predictive Power Q^2			0.105	0.015
Adjusted R^2			0.209	0.029
VIF		Minimum	1.188	
		Maximum	1.813	

Source: Authors' Compilation.

The path graph for the third model tested is given in Figure 4. In Figure 4, the following hypotheses have been tested.

H_{E1}: As individuals' experience increases, their RD levels increase.
Meaning that the more importance the participants gave to experience the more they agree on the way they define/identify risk.
H_{E2}: As individuals' experience increases, their RB levels also increase.
Meaning that the more importance the participants gave to experience the more they agree on the way they address and behave in the face of risk.

H_{E3}: As RD increases in individuals, RB also increases.
Meaning that the more the participants agree on the way they define and identify risk the more they agree on the way they address and behave in the face of risk.

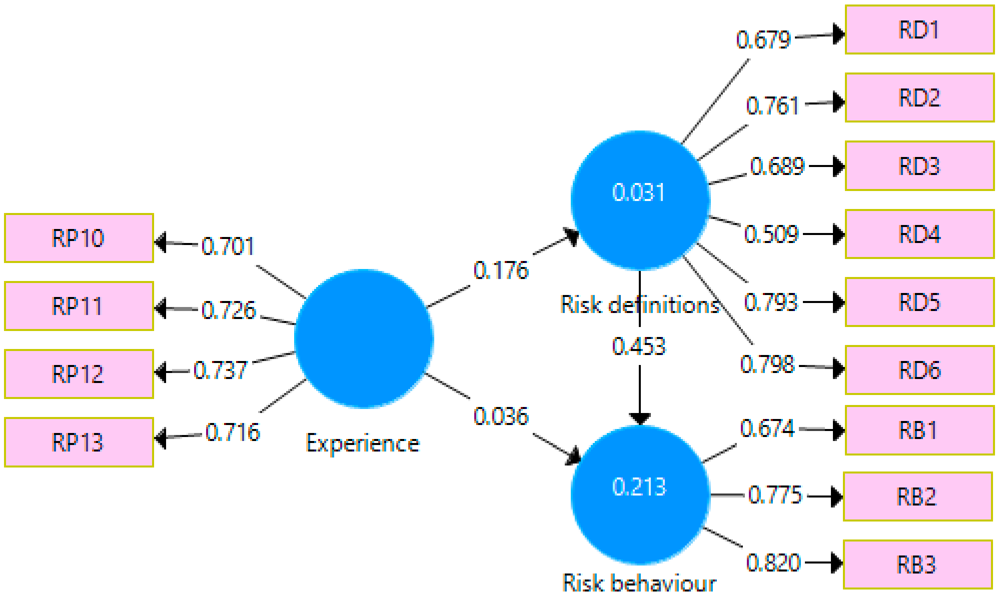

Figure 4. Model Three Structural Path Graph (Source: Authors' Compilation).

Figure 4 shows that:

- We observe a positive (β = 0.176) and statistically significant (t = 3.696, P = 0.000) causal effect of the social experiences of individuals on their RD. An increase in the agreement by participants on the experience level of individuals effects positively the agreement by participants on RD. So, H_{E1} has been supported.
- We observe a positive (β = 0.036) non-statistically significant (t = 0.593, P = 0.553) causal effect of the experience of individuals on the variable of RB. This relationship was not found to be statistically significant. Therefore, H_{E2} could not be supported.
- We observe a positive (β = 0.453) and statistically significant (t = 8.546, P = 0.000) causal effect of the RD level of individuals on their RB. An increase in the agreement by participants on RD level of individuals effects positively the agreement by participants on RB. As with model one, H_{E3} is supported on model three.

The predictive power of the RB variable for the third model was calculated as Q^2 = 0.105 and its prediction power was found to be low. Q^2 = 0.015 was calculated for the RB, but the calculated value was found to be less than the threshold value of 0.02. Looking at the R^2 values, it was determined that the experience of the individuals explained 2.9% of the RD variable and 20.9% of the RB variable. Looking at the f^2 values, it was determined that the experience variable had no effect in explaining the RB (f^2 = 0.002), but it was lowly effective in defining the risk (f^2 = 0.032). It was determined that the RD variable has a moderate effect (f^2 = 0.253) on RB.

In the fourth model, tested in the study, the knowledge level of individuals about risk was taken as the exogenous variable. The effect of the knowledge variable on RD and RB was examined. It was determined that there are indicators with a load value below 0.70 in factor loads in the model. Since AVE values are higher than the 0.50 threshold, these indicators have not been removed from the research model. In the fourth model, the reliability of the latent variables for internal consistency was examined, and it was determined that the Cronbach's Alpha and rho_A values of the RB variable were between 0.60 and 0.70. In other cases, since the reliability coefficients of all three variables were found to be greater than 0.70, it was understood that the internal consistency of the variables was provided. The fact that AVE values are above 0.50 for all three variables indicates that convergent validity is ensured. The discriminant validity of the model was also examined and it was determined that the Fornell-Larcker criterion and the HTMT coefficients met the criteria. According to the Fornell-Larcker criterion, the values above the diagonal were determined to be higher than the 0.70 threshold value. Similarly, it was determined that the values calculated in HTMT coefficients were 0.85 smaller and the discriminant validity was ensured. SRMR value, which is another fit measure, was calculated as 0.086 and found to be acceptable for the model. The fact that the maximum VIF value in the model was calculated as 1.813 shows that there is no multicollinearity between the variables.

Model results were given in Table 7.

Table 7. Evaluation of Reflective Measurement Models and Structural Models for Model Four.

		Knowledge	Risk Behaviour	Risk Definition
Knowledge		0.733		
Risk Behaviour		0.474	0.760	
Risk Definition		0.445	0.448	0.713
AVE		0.537	0.577	0.508
Rho_A		0.721	0.665	0.828
Cronbach's Alpha		0.713	0.636	0.802
Composite reliability (CR)		0.822	0.803	0.859
HTMT	Risk Behaviour	0.674	----	
	Risk Definition	0.578	0.602	----
SRMR		0.086		
Predictive Power Q^2			0.160	0.097
Adjusted R^2			0.295	0.198
VIF		Minimum	1.203	
		Maximum	1.813	

Source: Authors' Compilation.

The path chart for the fourth model is given in Figure 5 and the following hypotheses have been tested.

H_{K1}: As the level of knowledge of individuals about risks increases, their level of RD also increases.
Meaning that the more importance the participants gave to knowledge the more they agree on the way they define/identify risk.
H_{K2}: As the level of knowledge of individuals about risks increases, their RB levels also increase.
Meaning that the more importance the participants gave to knowledge the more they agree on the way they address and behave in the face of risk.
H_{K3}: As the RD level of individuals increase, the level of RB also increases.
Meaning that the more the participants agree on the way they define and identify risk the more they agree on the way they address and behave in the face of risk.

Figure 5 shows that:

- We observe a positive (β = 0.445) and statistically significant (t = 8.094 P = 0.000) causal effect of the knowledge level of the individuals on the RD variable. An increase in the agreement by participants on the knowledge level of individuals affects positively the agreement by participants on RD. Hence H_{K1} was supported.
- We observe a positive (β = 0.343) and statistically significant (t = 6.597 P = 0.000) causal effect of the knowledge level of individuals on the RB. This result indicates that an increase in the agreement by participants on the knowledge level of individuals affects positively the agreement by participants on RB. Hence H_{K2} was supported.

- We observe a positive (β = 0.295) and statistically significant (t = 5.976 P = 0.000) causal effect of the level of individuals' defining of risks on their level of risk management.
- This result indicates that an increase in the agreement by participants on the RD level of individuals affects positively the agreement by participants on RB. As with model one, model four H_{K3} is also supported.

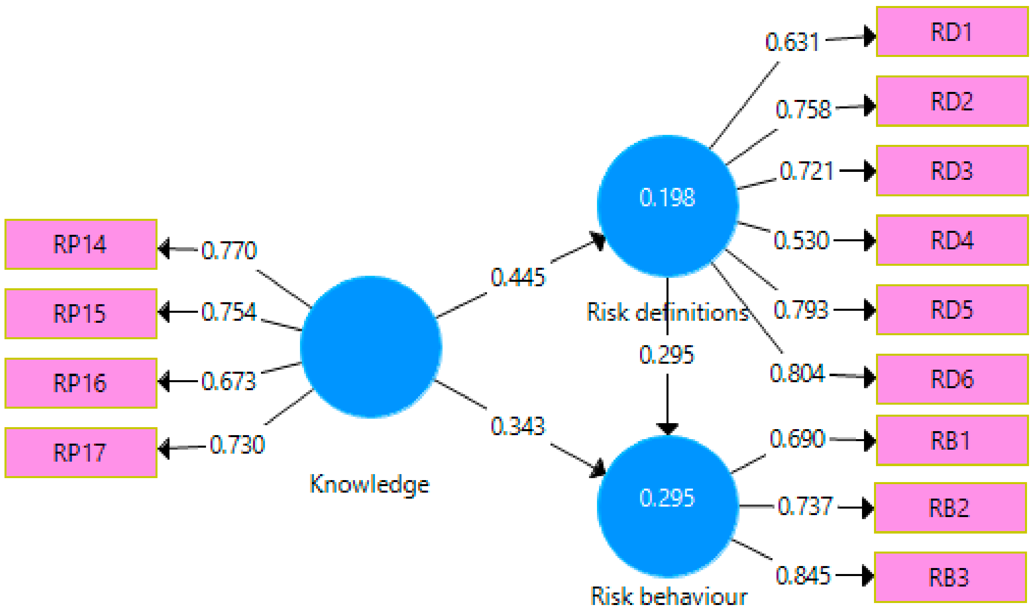

Figure 5. Model Four Structural Path Graph.

For the fourth model, the predictive power of the RB variable was calculated as Q^2 = 0.160 and the predicting power was found to be moderate. For RD, Q^2 = 0.097 was calculated and its predictive power was found to be low. Looking at the R^2 values, it was determined that the knowledge level of the individuals explained 19.8% of the RD variable and 29.5% of the changes in the RB variable. Looking at the f^2 values, it was determined that the knowledge variable had a low effect in explaining the RB (f^2 = 0.134), and the effect was moderate in RD (f^2 = 0.247). In addition, it was determined that the RD variable has a low effect on RB (f^2 = 0.099).

In the fifth model tested in the study, the peer influences variable was taken as an exogenous variable and the effect of the peer influence variable on RD and RB was examined. It was determined that there are indicators with a factor load value below 0.70 in the model. Since AVE values are higher than the 0.50 threshold, these indicators are included in the research model. In the model, the reliability of the latent variables for internal consistency was examined, and it was determined that the Cronbach's Alpha and rho_A values in the RB variable were between 0.60 and 0.70. In other cases, since the reliability coefficients in all three variables were found to be greater than 0.70, it was understood that the internal consistencies of the variables were provided.

For the fifth model, since AVE values were obtained above 0.50 for all three variables, convergent validity was provided. The discriminant validity was also examined, and it was determined that the Fornell-Larcker criterion and the HTMT coefficients met the criteria. According to the Fornell-Larcker criterion, values above the diagonal were determined to be higher than the 0.70 threshold value. Similarly, it was determined that the values calculated in the HTMT coefficients were lower than 0.85 and the discriminant validity was ensured. Another fit measure, SRMR value was calculated as 0.081 and was found to be acceptable for the model. The maximum VIF value was calculated as 1.813 and it was observed that there was no multicollinearity between variables.

Table 8 shows the critical values for model five.

Table 8. Evaluation of Reflective Measurement Models and Structural Models for Model Five.

	Peer Influences	Risk Behaviour	Risk Definition
Peer influences	0.803		
Risk Behaviour	0.068	0.758	
Risk Definition	0.261	0.455	0.713
AVE	0.645	0.575	0.508
Rho_A	0.724	0.659	0.818
Cronbach's Alpha	0.723	0.636	0.802
Composite reliability (CR)	0.845	0.801	0.859
HTMT Risk Behaviour	0.122	-----	
HTMT Risk Definition	0.354	0.602	----
SRMR	0.086		
Predictive Power Q^2		0.109	0.033
Adjusted R^2		0.206	0.066
VIF	Minimum	1.203	
VIF	Maximum	1.813	

Source: Authors' Compilation.

The path chart for the fifth model tested is given in Figure 6 and the hypotheses about it are shown as follows.

H_{P1}: Increasing peer influence on individuals increases RD.
Meaning that the more importance the participants gave to peer influence the more they agree on the way they define/identify risk.
H_{P2}: Increased peer influence on individuals increases RB as well.
Meaning that the more importance the participants gave to peer influence the more they agree on the way they address and behave in the face of risk.
H_{P3}: RB increases as individuals' RD level increases.
Meaning that the more the participants agree on the way they define and identify risk the more they agree on the way they address and behave in the face of risk.

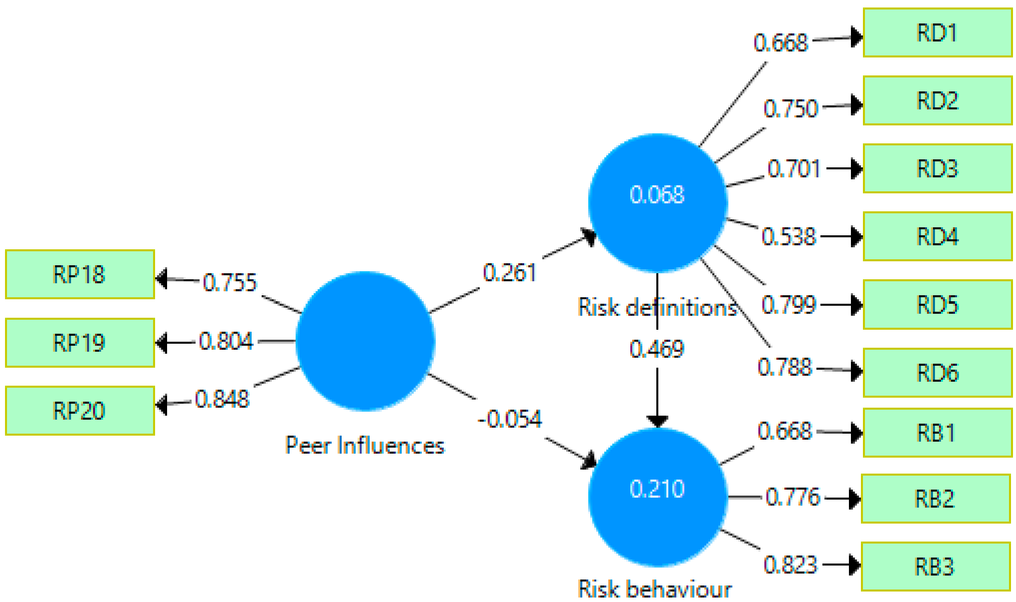

Figure 6. Model Five Structural Path Graph (Source: Authors' Compilation).

Figure 6 shows that:

- We observe a positive (β = 0.261) and statistically significant (t = 5.429, P = 0.000) causal effect of the level of peer influences of individuals on the level of RD. So, an increase in the agreement by participants on peer influences the level of individuals affects positively the agreement by participants on RD. Therefore, H_{P1} is supported.
- We observe a positive (β = 0.266) and non-statistically significant (t = 1.259, P = 0.214) causal effect of the level of peer influences of individuals on the RB variable. However, this relationship was found to be statistically insignificant. Therefore, H_{P2} is not supported.
- We observe a positive (β = 0.469) and statistically significant (t = 8.889, P = 0.000) causal effect of the RD variable on the RB in individuals. This result means that an increase in the agreement by participants on the RD level of individuals affects positively the agreement by participants on RB. As with Model one, H_{P3} was supported in model five.

The power to predict the RB variable for the fifth model was calculated and the power to predict was found to be low (Q^2 = 0.109). Q^2 = 0.033 was also calculated for RD and the predictive power was found to be low. Based on adjusted R^2 values, it was determined that the peer influences explained 6.6% of the changes in the RD variable and 20.6% of the changes in the RB variable. When looking at f^2 values, it was determined that the exposure of individuals to peer influence had no significant effect on the explanation of RB (f^2 = 0.003) and that it was low in the definition of risk (f^2 =0.073). It was determined that the effect of RD on RB was moderate (f^2 = 0.260).

In the sixth model tested the openness property of individuals as an exogenous variable was considered, and its effect on RD and RB was analysed. In the model, it was determined that there were indicators with a load value below 0.70 in factor loads. Also, since AVE values are higher than the 0.50 threshold, these indicators are not excluded from the research model.

In the sixth model, rho_A and Cronbach's Alpha statistics of openness and RB variables were calculated below 0.70, while in the RD variable, values higher than 0.70 were obtained. Similarly, since the Composite reliability value is calculated higher than 0.70 for all three variables, it is decided that the internal consistency of the variables is achieved. Since the AVE values for the sixth model are obtained above 0.50 for all three variables, convergent validity is also provided. It has been determined that the Fornell-Larcker criterion (>0.70) and HTMT coefficients (<0.85) provide the criteria for discriminant validity. The SRMR value was also calculated at 0.084 and found to be acceptable for the model. The maximum VIF value is 1.813 and there is no multicollinearity between variables. We can see the results in Table 9.

The path graph for the sixth model is given in Figure 7 and the following hypotheses are tested.

H_{O1}: RD increases as individuals' openness increases.
Meaning that the more importance the participants gave to openness the more they agree on the way they define/identify risk.
H_{O2}: As individuals' openness increases, RB also increases.
Meaning that the more the participants agree on the way they define and identify risk the more they agree on the way they address and behave in the face of risk.
H_{O3}: RB also increases, while the degree of RD of individuals increases.
Meaning that the more the participants agree on the way they define and identify risk the more they agree on the way they address and behave in the face of risk.

Table 9. Evaluation of Reflective Measurement Models and Structural Models for Model Six.

		Openness	Risk Behaviour	Risk Definition
Openness		0.714		
Risk Behaviour		0.108	0.759	
Risk Definition		0.094	0.462	0.711
AVE		0.510	0.577	0.505
rho_A		0.558	0.654	0.827
Cronbach's Alpha		0.545	0.636	0.802
Composite reliability (CR)		0.755	0.802	0.857
HTMT	Risk Behaviour	0.181	-----	
	Risk Definition	0.133	0.602	----
SRMR		0.084		
Predictive Power Q^2			0.114	0.003
Adjusted R^2			0.214	0.007
VIF		Minimum	1.125	
		Maximum	1.813	

Source: Authors' Compilation.

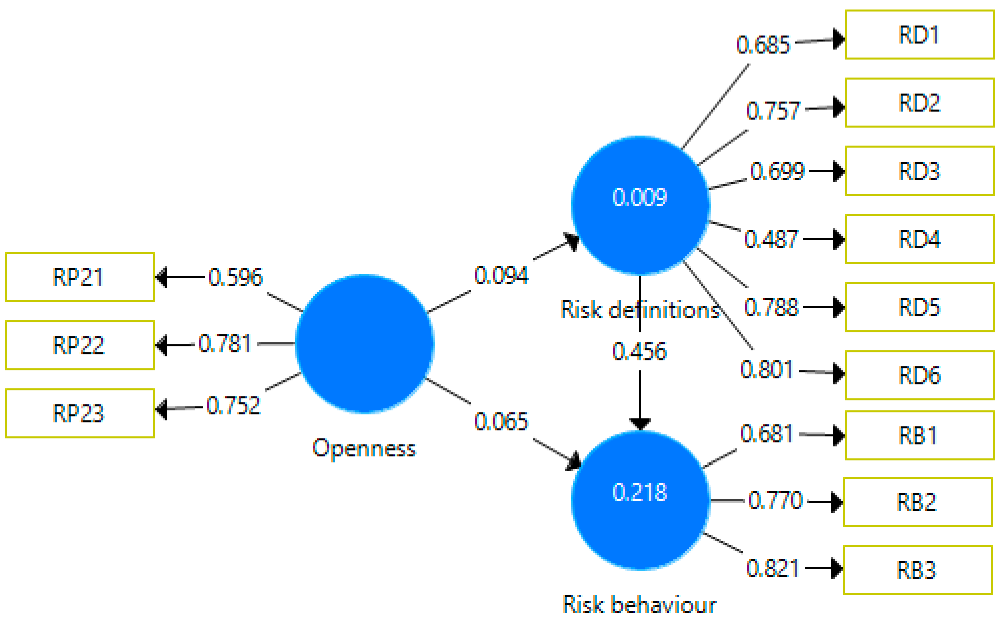

Figure 7. Model Six Structural Path Graph (Source: Authors' Compilation).

Figure 7 shows that:

- We observe a positive (β = 0.094) and statistically significant (t = 1.516, P = 0.130) causal effect of the openness levels of individuals on the RD levels but this was not statistically significant and H_{O1} is not supported.
- We observe a positive (β = 0.065) and non-statistically significant (t = 1.069, P = 0.285) causal effect of the openness of individuals on the RB. Therefore, H_{O2} is not supported.
- We observe a positive (β = 0.456) and statistically significant (t = 8.792 P = 0.000) causal effect of the risk identification level of individuals on the RB. Accordingly, an increase in the agreement by participants on the RD level of individuals affects positively the agreement by participants on RB. As with model one, H_{O3} was supported in model six.

In the sixth model, the power to predict the RB variable was calculated as Q^2 = 0.114 and found to be low. Q^2 = 0.003 was calculated for RD and it was determined that there was no predicted power. According to adjusted R^2 values, the RD variable of individuals describes 21.8% of the change in the RB variable. It was determined that the effect of RD on RB was moderate ($f^2 = 0.263$).

8. Conclusions

The main purpose of the study was to investigate the effect of RP and RD on the RB (i.e., Risk Management) of individuals during an unprecedented (Covid -19) period when no solution was yet available. In this paper, we explored how people perceive risk, how they define it and how they behave and address it. Building on existing research, we have presented six dimensions of RP and tested 18 hypotheses using six structural models. The conceptual framework was based on secondary data obtained from part of a survey designed and conducted by two authors for a previously unpublished study (Girlando 2020) and a published chapter by Girlando et al. (2021). However, due to the complexity and variations in the way individuals perceive and define risk it is important for policy makers in both the public and private sector to know the effect of the RP and RD on RB. This study adds to body of literature and sheds new light on the interaction between RP, RB and RD in a time of distress. It provides important and original information that may be useful for government agencies, businesses, individuals and the media when setting policies, governance structures, regulations, procedures and determining how to communicate. After looking at the various literature summarised above, we expect a similar relationship, but with a different impact, between the participants' agreement on RP, RD and RB, because RP includes different sub-dimensions, specifically Religion and Beliefs, Fear, Experience, Knowledge, Peer Influences and Openness.

In fact, although we expected that the relation between the agreement by participants on the RP and RB and RD will vary in their impact (since for example, bad experiences has a larger impact than favourable experiences and there can be a two-way relationship between for example openness and fear), our expectations derived from the literature review above were that, for example, agreement by participants on the RP (i.e., religion and beliefs, fear, experience, knowledge, peer influences and openness) affect the agreement on the approach in RB and the agreement on the way that participants identify RD positively and vice versa.

Our findings show that there is no direct relationship between the agreement by participants' on the perception of "religion and beliefs" and the agreement on the RB, the agreement by participants' on the perception of the "fear level" and the agreement on the RB, the agreement by participants' on the perception the "experience" and the agreement on RB, the agreement by participants' on the perception on "peer influences level" and the agreement on RB and the agreement by participants' on the perception on openness and the agreement on RB. However, a positive relationship was found between the agreement by participants on the perception of "knowledge" and the agreement on the RB approach. There are statistically significant relationships between the agreement by participants on the perception of "religion and beliefs" and the agreement on the RD, the agreement by participants on the perception on "fear level" and the agreement on RD, the agreement by participants' on the perception "experience" and the agreement on RD, the agreement by participants' on the perception "knowledge" and the agreement on RD and the agreement by participants' on the perception "peer influences level" and the agreement on RD. For each model, there is a moderate but significant relationship between the agreement on the RD and the agreement on the RB approach. Moreover, there is an indirect relationship when controlling for the agreement on RD between the agreement by participants on the perception "fear level and the agreement on the RB approach", the agreement by participants' on the perception "experience" and the agreement on RB, the agreement by participants' on the perception "knowledge" and the agreement on the RB approach and the agreement by participants' on the perception "peer influences level" and the agreement on the RB approach. However, there is no relationship between the agreement by participants on the perception of "openness" and the RB approach.

Although, our approach and method may pose some limitations on the generalisability of our findings since they are skewed to our friends on social media, the fact that we have gathered more than the sufficient sample size for such a study and that we also used the non-probability snowballing sampling gives us more confidence that the network chosen for our sample is much more open. Also, we used a different approach from other authors to carry out our study, delve into more detail on the specific RPs and determine whether these findings corroborate or not with previous authors' findings.

Even though there is ample research on RP, to our knowledge, there are limited studies carried out on RP, the influencing factors and the agreement on RB and RD. Also, another limitation could be the period when the data was extracted. Since people perceive risks differently per their religious belief, fear, knowledge, experiences, peer influence and openness, any previous views individuals had on risk could have been altered during the period of the COVID-19 pandemic. However, this can be seen in a positive light since it provides important and original information for authorities, businesses and individuals as well as the media. This information is crucial to understand how the public judge risk, how they behave toward risk as well as the factors that influence their RP, to make effective decision-making, foresee the public's responses to risk and communicate risk during a highly uncertain period, where no solution was yet expected. This knowledge could improve people's RP, RD and RB, including successful risk communication. As a result, knowing what influences RP, RD and RB can help in encouraging people to make the right decisions, act accordingly and appreciate the need for business continuity planning to ensure sustainability and what we humans consider as normality. When lacking adequate information one must rely on the risk judgments of authorities and the experts and the knowledge of our findings on the public's RP and impact on RD and RB can help the way policymakers assess and take decisions on risks.

In fact, when you study deeper into RP, our findings corroborate only to a certain extent, to the findings of most authors such as Galizzi and Tempesti (2015), Weber et al. (2002), Furby and Beyth-Marom (1992) and Byrnes et al. (1999), who as noted above stated that an individual can participate in risky behaviour when s/he is not aware of the consequences and that if a person understands and defines risk, s/he can avoid and manage his/her risks, t. When the risk-addressing person is aware of negative outcomes, s/he can avoid the risk. They show that the expectation is that persons with similar risk perceptions will define risk and address risk in a similar way and vice versa. We show, however, that this is not always the case since in most cases, the RP on religion and beliefs, the fear level, experience, peer influences level and openness and the agreement on the RB approach do not show a relationship. Also, there is no relationship between the agreement by participants' on the perception of "openness" and the RB approach.

Therefore, similarly to what Slovic (2010) suggests, we need to understand how individuals think and feel when faced with uncertainties. Understanding their cognitive process will help us determine how individuals and societies can improve their risk perception and decrease the noise that dampens their judgment on risk. Therefore, this paper contributes to the current literature, especially since it reflects data during a time of uncertainty (the COVID-19 pandemic period) and findings can confirm or otherwise the way individuals define and perceive risk and behave. Knowledge of this is important for policymakers who need to ensure sustainability, by ensuring a balance between economic, societal and environmental factors.

Moreover, we agree with Girlando et al. (2021) that effective risk information communicated to the public and private policymakers are important so that they can determine the most appropriate and effective action for the public's interest, building people's trust, planning to avoid national emergencies and to improve the public's RB and attitudes toward risk. Research on RP can help acquire this understanding. This study recognizes a need for RP, RD and RB and models to be in place so that authorities may educate the public, especially for the timely identification of potential risks and their address. Getting this correct, could have saved several lives and jobs especially during the current COVID pandemic.

Furthermore, this study recognises the human being, who perceives risk, identifies it and makes decisions on the way to address it based on their limited knowledge and experiences. Also, it must be emphasized that developing models and rules to identify and approach risk are important, but we need to be able also to understand the assumptions of these models and their risk if we are to achieve sustainability and a balance between social needs, economic needs and the environment.

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Appendix A

Table A1. Summary Statistics of Responses.

	Min.	Max.	Mean	Std. Deviation	Median	Skewness	Kurtosis
RD1	1	5	1.98	1.027	2	1.177	1.105
RD2	1	5	2.02	0.899	2	1.046	1.373
RD3	1	5	2.06	0.992	2	0.925	0.650
RD4	1	5	2.83	1.109	3	0.040	−0.710
RD5	1	5	2.13	0.969	2	0.802	0.283
RD6	1	5	1.97	0.887	2	0.848	0.680
RB1	1	5	1.80	0.829	2	1.268	2.115
RB2	1	5	1.95	0.908	2	1.074	1.366
RB3	1	5	1.45	0.726	1	1.846	3.797
RP1	1	5	2.86	1.082	3	0.100	−0.591
RP2	1	5	3.10	1.322	3	0.017	−1.154
RP3	1	5	3.26	1.325	3	−0.087	−1.159
RP4	1	5	2.93	1.249	3	0.130	−1.006
RP5	1	5	2.55	1.194	2	0.542	−0.552
RP6	1	5	2.96	1.186	3	0.126	−0.915
RP7	1	5	2.92	1.184	3	−0.026	−0.918
RP8	1	5	3.23	1.164	3	−0.221	−0.821

Table A1. *Cont.*

	Min.	Max.	Mean	Std. Deviation	Median	Skewness	Kurtosis
RP9	1	5	2.65	1.134	2	0.216	−0.948
RP10	1	5	1.86	0.854	2	1.099	1.515
RP11	1	5	2.18	0.889	2	0.723	0.516
RP12	1	5	1.92	0.818	2	0.934	1.106
RP13	1	5	1.85	0.791	2	0.963	1.325
RP14	1	5	1.76	0.875	2	1.328	1.964
RP15	1	5	1.78	0.882	2	1.462	2.647
RP16	1	5	2.08	0.913	2	0.787	0.495
RP17	1	5	2.08	0.870	2	0.763	0.584
RP18	1	5	3.36	1.324	4	−0.199	−1.268
RP19	1	5	3.24	1.222	3	−0.116	−1.086
RP20	1	5	3.24	1.234	3	−0.126	−1.103
RP21	1	5	2.55	1.156	2	0.380	−0.721
RP22	1	5	2.06	0.964	2	0.862	0.253
RP23	1	5	1.95	0.837	2	0.690	0.224

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