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DETERMINATION OF FACTORS AFFECTING HUMANITARIAN LOGISTICS RESILIENCE UNDER DELAYED AID DISTRIBUTION

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ABSTRACT

Resilience in the face of delays in the distribution of humanitarian logistics is a crucial aspect in post-disaster response. This study aims to analyze the factors that affect the resilience of disaster victims in the context of logistics delays using the Partial Least Squares Structural Equation Modeling (PLS-SEM) approach. This research model adopts three main constructs, namely Sense of Mastery (SoM), Sense of Relatedness (SoR), and Emotional Reactivity (ER), which are assumed to contribute to individual resilience (RES). Data was collected through a questionnaire-based survey of individuals who had experienced delays in the distribution of humanitarian aid. The results of the analysis show that SoM and SoR have a significant positive influence on resilience. In contrast, ER has a negative relationship with RES, which means that the higher a person's level of emotional reactivity, the lower their level of resilience in the face of delays in help. In the initial model, there are several indicators showing low outer loading values so they are excluded from the final model, because they do not contribute significantly to other variables. After refining the model, the reliability results show that the remaining constructs have good validity and reliability values. Strong R-square values for all endogenous variables (SoM = 0.962, SoR = 0.894, ER = 0.981, RES = 0.944) confirm that the model has high predictive ability in explaining resilience in the context of delays in the distribution of human logistics. The results of this study can be the basis for policymakers and stakeholders in developing a more optimal aid distribution system, as well as mitigation strategies that can increase the resilience of disaster victims in facing future logistical challenges.

Keywords: Resiliency, logistics delays, PLS-SEM, humanitarian logistics

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1. INTRODUCTION

Indonesia is one of the countries that is included in the category of vulnerable to various kinds of natural disasters, both in the form of volcanic eruptions, earthquakes, landslides, tsunamis, floods, and others. According to data from Statista Research Department (2023), there were at least 3.5 thousand natural disasters in Indonesia, where this number increased from 2021, namely 2.95 thousand disasters that caused 1,006 deaths, 1,443 injuries, 3,034,000 displaced, and 1,700,000 affected victims (Puspitasari et al., 2019). In general, disasters cause physical damage such as infrastructure damage, physical injury, loss of life, and others. In addition, disasters can also cause prolonged social and economic disruption where disaster victims often have to face loss of sources of income, jobs, access to health services, and long-term economic recovery.

However, not limited to physical damage, disasters can also have a significant impact on the psychological, social, and welfare of people affected by disasters (Shultz et al., 2013). The psychological damage left behind by tsunamis, earthquakes, droughts, volcanic eruptions, conflicts, and so on has proven to be just as devastating as physical damage. A study found that natural disasters can increase the risk of mental health disorders including PTSD (post-traumatic stress disorder), anxiety, and depression especially in more vulnerable populations such as the elderly and children, which contributes to the low resilience of individuals post-disaster (Obuobi-Donkor et al., 2022).

Resilience is the ability of an individual or group to adapt well in the midst of challenging, threatening, or dangerous situations (Leonard, 2022). Resilience is one of the key factors in helping individuals and communities to be able to bounce back after a disaster occurs. Resilience can be affected by a variety of factors, such as social support, coping skills, optimism, hope, and others. Low resilience can cause individuals or groups to become easily stressed, depressed, traumatized, or even suicidal (Apriyanto and Setyawan, 2020; Lee, 2024; Lee et al., 2022; Leonard, 2022).

One of the factors that can affect the resilience of victims of natural disasters is the fulfillment of basic needs such as clothing, food, water, shelter, and access to health services and facilities. These basic needs are primary needs that must be met in order for individuals or groups to survive and maintain their quality of life (Puspitasari et al., 2019). The fulfillment of these basic needs is generally carried out through the distribution of logistical assistance from the government, humanitarian institutions, or the local communities. However, the distribution of this logistical aid often encounters obstacles, such as delays, inadequacies, inadequacies, or inequalities in the distribution of disaster aid.

Studies have shown that although many people show resilience when facing difficulties in life (Friedman and Kern, 2014)), there are also those who are unable to develop such positive adaptations (Bonanno, 2005). Various studies related to resilience, especially in post-disaster situations, have been carried out. A study that has been conducted related to the identification of factors that affect the resilience of victims of natural disasters is by using the in-depth interview (IDI) approach. The study shows that factors such as social support, trust in those who provide assistance, and access to basic needs greatly affect the level of resilience of individuals (Kusumastuti, 2012). Psychological factors such as optimism, self-efficacy, and adaptability also play an important role in improving the resilience of disaster victims (Leipold and Greve, 2009).

Another study that focuses on the level of resilience of tsunami victims was carried out using a statistical approach, namely multiple regression analysis. From this study, it was found that individuals who have strong social support tend to be more able to overcome challenges that arise after a disaster occurs (Sasmita and Afriyenti, 2019). In addition, there is a study that focuses on the analysis of resilience of victim communities affected by disasters by applying the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) approach (Tariq et al., 2021) and statistical analysis methods, namely the Random Effect Model which shows that it shows that effective coping strategies also affect individuals' ability to adapt to post-disaster conditions (Gim and Shin, 2022).

Structural Equation Modeling (SEM) is one of the various reliable analysis methods to analyze the influencing factors in the part of the mitigation process and actionable action plans related to disasters (Ong et al., 2022). This approach is particularly valuable in capturing the complex interrelationships among behavioral, psychological, and systemic variables in post-disaster contexts. Some of the studies that have been conducted using the SEM method are to analyze community preparedness factors for volcanic disasters (Ong et al., 2023) and typhoon disasters (Gumasing et al., 2022) in the Philippines, revealing how psychosocial and environmental variables shape response outcomes. Expanding this methodological application, a study developed by Khan et al. (2022) investigate resilience and performance in humanitarian logistics. SEM was used to explore how digital technologies influence humanitarian supply chain responsiveness, highlighting resilience as a mediating factor between digital capability and logistical efficiency.

While prior studies have focused on community-level preparedness and supply chain optimization, the present study applies SEM to explore resilience behavior among disaster victims—particularly in the context of delayed humanitarian aid and the fulfillment of basic needs. Therefore, this study aims to analyze what factors affect the resilience of disaster victims, especially related to the smooth distribution of humanitarian aid as an effort to meet the basic needs of disaster victims by applying SEM using SmartPLS to analyze the relationships between key resilience determinants and the efficiency of humanitarian logistics. By understanding these factors, it is hoped that the government and non-governmental organizations and related parties can develop more effective strategies to distribute disaster relief so that they can increase community resilience in facing disasters in the future.

2. METHODS

2.1. Measurements

The number of questionnaires distributed during the study was as many as 300 copies assuming that invalid data was possible, where the estimated number of respondents recommended to get stable results was around 200 respondents (Ghozali, 2016). And the final valid data that was successfully collected for processing was as many as 191 data.

The technique used in sampling is *non-probability sampling* with *the purposive sampling* method. *Purposive sampling* is a *sampling* technique that uses the researcher's assessment to determine the sample that matches the characteristics needed in the research (Ferdinand, 2014). In this study, the criteria used were that respondents were victims of natural disasters that had occurred in the Special Region of Yogyakarta and received basic needs assistance during the recovery period. In this study, the criteria used were that respondents were victims of natural disasters that had occurred in the Special Region of Yogyakarta and received basic needs assistance during the recovery period.

2.2 Questionnaire

The questionnaire applied in this study was based on the Resiliency Questionnaire for Adults (RQA), a standardized and psychometrically validated instrument developed by Sandra Prince-Embury. This questionnaire was developed for research as a derivative of the original (Resiliency Scale for Children and Adolescents – RSCA) (Prince-Embury, 2007). The RQA is widely recognized for its strong theoretical foundation and reliability in measuring key resilience constructs, including Sense of Mastery (SoM), Sense of Relatedness (SoR), and Emotional Reactivity (ER).

Given its established validity in previous research, the instrument was directly applied without the need for additional validation procedures. The indicators assessed in this study are nine latent variables, with four indicators used for each latent. These latent variables include self-efficacy, optimism, adaptability, trust, support, comfort, tolerance, sensitivity, and impairment. Each indicator is measured using a 5-point Likert scale (1 = strongly disagree to 5 = strongly agree). Each latent variable is then arranged with question indicators adjusted to the conditions of disaster relief logistics delays as can be seen in Table 1.

Table 1. Disaster Victim Resilience Instrument

Latent variables	Indicators	Question
Optimism	OPT1	I remain optimistic that aid will arrive despite the delay.
	OPT2	I often worry that late aid may not be enough when needed.
	OPT3	When faced with delays in aid, I tend to think that the situation will improve.
	OPT4	I often feel that the situation gets worse when aid doesn't come on time.
Self-Efficacy	SE1	I felt helpless when the help we needed didn't arrive on time.
	SE2	I am confident that I can handle difficult situations even if aid comes late.
	SE3	When aid is late, I often feel like there's little I can do.
	SE4	Despite the delay in aid, I am confident that I can make the right decision for survival.
Adaptability	ADP1	I was able to adapt to the situation despite the delay in receiving aid.
	ADP2	Every time I faced a delay in help, I found it difficult to adapt.
	ADP3	I was flexible enough to adapt to the new situation despite the delay in help.
	ADP4	I had trouble adjusting to the frequent delays in aid.
Trust	TRU1	I often feel that the responsible party is taking advantage of emergency situations.
	TRU2	I believe that the responsible parties will help us even if it is sometimes too late.
	TRU3	I often feel ignored by the responsible party in emergency situations.
	TRU4	I am sure that most people will try to help in an emergency even if there is a delay.
Social Support	SUP1	I have a strong support network that helps me overcome aid delays.
	SUP2	I often feel like I have nothing to rely on when aid comes late.
	SUP3	There are a few people I can share in about my frustration regarding delays in aid.
	SUP4	I often feel alone in the face of delays in aid.
Emotional Comfort	COM1	I have difficulty interacting with others when I feel frustrated due to delays in aid.
	COM2	I feel comfortable expressing my disagreement about the way the delay in aid is handled.
	COM3	I often feel uncomfortable in the middle of a crowd of people who are also waiting for aid.
	COM4	I usually feel calm and can blend in with others even in situations waiting for aid.
Tolerance	TOL1	I quickly forgive the mistake in handling the aid late.
	TOL2	I have a hard time saying my disagreement about the delay in aid in a polite way.

Latent variables	Indicators	Question
	TOL3	Saya terbuka untuk memahami berbagai alasan di balik keterlambatan bantuan.
	TOL4	I am open to understanding the various reasons behind the delay in aid.
Sensitivity	SEN1	The delay in aid immediately frustrated me.
	SEN2	There were many things during the delay in aid that made me feel depressed.
	SEN3	I was easily get angry and defensive when the promised aid was too late.
	SEN4	Others find it hard to see me angry or depressed because of the delay in aid.
Impairment	IMP1	I was able to think clearly and remain calm even though the aid was late.
	IMP2	I tend to make mistakes when I'm stressed out due to delays in aid.
	IMP3	I can think clearly and remain rational even when faced with delays in aid.
	IMP4	Delays in aid often prevented me from concentrating or making good decisions.

2.3 Partial Least Squares- Structural Equation Model (PLS-SEM)

The data that has been collected from the survey is then analyzed with multivariate analysis, specifically using Smart-PLS. PLS-SEM is applied to the collected data to analyze the relationship between factors affecting individual resilience in the context of delays in the distribution of humanitarian logistics.

Furthermore, to see the quality of the model that has been made, several criteria are used in accordance with the standards required in PLS-SEM. The validity of convergence was evaluated through Outer Loading (OL) and Average Variance Extracted (AVE) values. A loading factor in the range of 0.6 to 0.7 is considered valid, while an AVE value of > 0.50 indicates that the construction has good validity. The validity of the discrimination was tested using the Fornell-Larcker criterion, where the AVE value must be greater than the correlation between dimensions in the model. To ensure reliability, the study relied on Alpha Cronbach's and Composite Reliability, with a threshold value of > 0.70, which indicates that the construction has good internal consistency (Hair et al., 2017).

In addition, the significance of the relationship between variables was tested using T-statistics and P-values. A relationship is considered significant if the T-statistics value is greater than the T-table and the P-values < 0.05. Finally, R-Square (R^2) was used to measure the predictive power of exogenous variables against endogenous variables, with categories of 0.25 as weak, 0.50 as moderate, and 0.75 as strong (Hair et al., 2017). With this approach, the research ensures that the developed model has sufficient validity, reliability, and predictive power to explain the relationships between variables in resilience analysis.

3. FINDINGS AND DISCUSSION

3.1. Findings

To build a conceptual model, this study uses a second-order construct approach to capture the complexity of relationships between variables in measuring resilience. The model includes three main mediating constructs that play a role in bridging the relationship between exogenous variables and endogenous variables. The nine main latent variables of resilience are grouped into three main dimensions.

Sense of Mastery (SoM) functions as a mediator that connects Optimism (OPT), Self-Efficacy (SE), and Adaptability (ADP) to Resilience (RES), showing that individuals who have higher optimism, self-efficacy, and adaptability tend to have a strong sense of control in facing challenges. Meanwhile, the Sense of Relatedness (SoR) acts as a mediator between Support (SUP), Comfort (COM), Tolerance (TOL), and Trust (TRU) towards RES, emphasizing the role of social relationships in strengthening individual resilience. Emotional Reactivity (ER) serves as a link between Sensitivity (SEN) and Impairment (IMP) to RES, indicating that a person's level of sensitivity and limitations in managing emotions can affect their level of resilience (Bonanno, 2005; Friedman and Kern, 2014; Leipold and Greve, 2009; Prince-Embury, 2007). The following Table 2 shows a summary of the variables used in the model:

Table 2. Recapitulation of Variables in Models

Variable	Type	Role in the model
Optimism (OPT)	Exogenous	Influencing SoM
Self-Efficacy (SE)	Exogenous	Influencing SoM
Adaptability (ADP)	Exogenous	Influencing SoM
Trust (TRU)	Exogenous	Affecting SoR
Support (SUP)	Exogenous	Affecting SoR
Comfort (COM)	Exogenous	Affecting SoR
Tolerance (TOL)	Exogenous	Affecting SoR
Sensitivity (SEN)	Exogenous	Affecting ER
Impairment (IMP)	Exogenous	Affecting ER
Sense of Mastery (SoM)	Mediator	Mediating the relationship between OPT, SE, ADP and RES
Sense of Relatedness (SoR)	Mediator	Mediating the relationship between OPT, SE, ADP and RES
Emotional Reactivity (ER)	Mediator	Mediating the relationship between OPT, SE, ADP and RES
Resilience (RES)	Endogenous	Key variables affected by SoM, SoR, and ER

With this approach, models can more accurately capture the psychological processes underlying individual resilience, while reducing bias due to direct relationships that may not fully reflect the actual mechanism. Figure 1 below is the initial model according to the theory used.

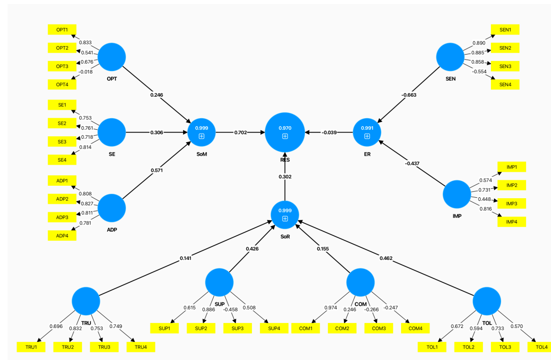

Figure 1. Initial model

From the initial model that has been made, it can be seen that the results of the outer loading are formed as seen in Table 3. Based on the results of the outer loading analysis, it is found that some indicators have values below the threshold of 0.7, so they must be removed to improve the validity of the model. In particular, all indicators of the COM construct have low values except COM1, even some indicators such as COM2 (-0.290) and COM3 (-0.322) have negative values. This suggests that the dimension of emotional comfort in the context of logistics distribution delays is not strong enough to be measured as an independent construct.

By referring to the results of the outer loading evaluation, the model is then modified to ensure that only the indicators/variables that represent the actual state are used in the model. Table 3 not only shows the outer loading of the initial model, but also summarizes the results of the outer loading of the final model to show the before and after comparison and show which indicators or variables were removed.

Table 3. Indicators statistical analysis

Name	Mean	Standard deviation	Outer Loading	
			Initial	Final
OPT1	3.723	0.813	0.833	0.909
OPT2	2.623	1.066	0.541	-
OPT3	3.314	1.006	0.676	0.751
OPT4	2.916	1.136	-0.018	-
SE1	3.037	1.040	0.753	0.739

Name	Mean	Standard deviation	Outer Loading	
			Initial	Final
SE2	3.702	0.892	0.761	0.775
SE3	3.016	1.123	0.718	0.703
SE4	3.749	0.909	0.814	0.824
ADP1	3.759	0.840	0.808	0.809
ADP2	3.230	1.013	0.827	0.824
ADP3	3.607	0.849	0.811	0.816
ADP4	3.257	0.988	0.781	0.777
TRU1	3.031	1.048	0.696	0.695
TRU2	3.775	0.757	0.832	0.836
TRU3	3.257	1.014	0.753	0.754
TRU4	3.791	0.879	0.749	0.746
SUP1	3.063	1.011	0.615	0.794
SUP2	3.283	0.978	0.886	0.864
SUP3	3.335	0.961	-0.458	-
SUP4	3.686	0.841	0.508	-
COM1	3.492	1.106	0.974	-
COM2	2.979	0.904	0.246	-
COM3	3.052	1.001	-0.266	-
COM4	3.796	0.828	-0.247	-
TOL1	3.508	0.932	0.672	0.780
TOL2	2.859	0.990	0.594	0.542
TOL3	3.634	0.807	0.733	0.787
TOL4	3.419	1.004	0.570	-
SEN1	3.482	1.017	0.890	0.912
SEN2	3.377	1.036	0.885	0.896
SEN3	3.613	1.006	0.858	0.862
SEN4	2.602	0.937	-0.554	-
IMP1	3.712	0.835	0.574	0.556
IMP2	3.670	0.875	0.731	0.732
IMP3	3.806	0.744	0.448	-
IMP4	3.304	1.050	0.816	0.844

Outer initial loading values of less than 0.5 are generally removed to produce a better model. In addition, it is possible that an outer loading value of more than 0.5 can also be removed if it does not show a significant influence on the overall model. After selecting the entire outer loading, the model is reshaped with variables that support the final model.

The final model can be seen in Figure 2 below:

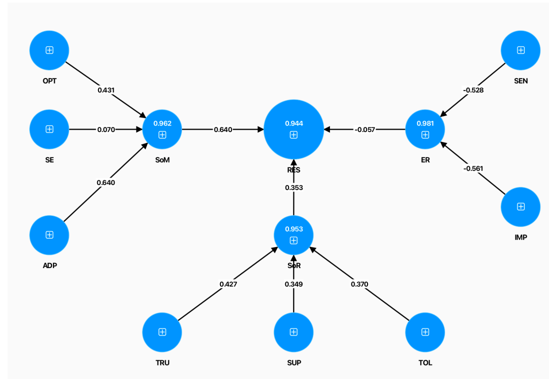

Figure 2. Final Model

After forming the finel model, the analysis was carried out by applying bootsraping calculations with the results summarized in the next few tables.

In the direct, indirect, and total effects analysis shown in Table 4, most of the relationships in the model had significant effects with a p-value of < 0.05, indicating that the relationships between variables had high statistical significance. ER → RES showed a significant negative effect (β = -0.057, p-value = 0.007), indicating that increased Emotional Reactivity (ER) can have a negative impact on logistical resilience (RES).

SoM → RES has a significant direct effect (β = 0.640, p-value = 0.000), which suggests that Sense of Mastery (SoM) plays an important role in improving logistics resilience. The SoR → RES also have a significant direct relationship (β = 0.353, p-value = 0.000), which suggests that Sense of Relatedness (SoR), such as social support and communication, plays a role in maintaining the resilience of logistics distribution.

Indirect effects also show significant influences, such as ADP → RES which have an indirect effect of 0.409 (p-value = 0.000), suggesting that individual adaptation to uncertain conditions has a significant contribution to logistical resilience through mediation pathways.

Table 4. Direct, indirect, and total effects

	Direct effect	P value	Indirect effect	P value	Total Effect	P value
ADP → SoM	0.640	0.000	-	-	0.640	0.000
ER → RES	-0.057	0.007	-	-	-0.057	0.007

	Direct effect	P value	Indirect effect	P value	Total Effect	P value
IMP → ER	-0.561	0.000	-	-	-0.561	0.000
OPT → SoM	0.431	0.000	-	-	0.431	0.000
SE → SoM	0.070	0.011	-	-	0.070	0.011
SEN → ER	-0.528	0.000	-	-	-0.528	0.000
SUP → SoR	0.349	0.000	-	-	0.349	0.000
SoM → RES	0.640	0.000	-	-	0.640	0.000
SoR → RES	0.353	0.000	-	-	0.353	0.000
TOL → SoR	0.370	0.000	-	-	0.370	0.000
TRU → SoR	0.427	0.000	-	-	0.427	0.000
ADP → RES	-	-	0.409	0.000	0.409	0.000
IMP → RES	-	-	0.032	0.007	0.032	0.007
OPT → RES	-	-	0.276	0.000	0.276	0.000
SE → RES	-	-	0.045	0.013	0.045	0.013
SEN → RES	-	-	0.030	0.007	0.030	0.007
SUP → RES	-	-	0.123	0.000	0.123	0.000
TOL → RES	-	-	0.131	0.000	0.131	0.000
TRU → RES	-	-	0.151	0.000	0.151	0.000

The reliability of the model shown in Table 5 is indicated by Cronbach's Alpha and Composite Reliability (CR) values which mostly meet the threshold criteria (CR > 0.70).

Table 5. Composite reliability

	Cronbach 's α	AVE	CR
OPT	0.579	0.695	0.819
SE	0.760	0.580	0.846
ADP	0.821	0.651	0.882
TRU	0.755	0.577	0.844
SUP	0.550	0.688	0.815
TOL	0.503	0.507	0.750
SEN	0.869	0.793	0.920
IMP	0.529	0.519	0.759
SoM	0.691	0.762	0.865
SoR	-0.765	0.740	0.515
ER	0.732	0.788	0.882
RES	0.842	0.618	0.889

SEN, SoM, ER, and RES constructs have excellent reliability with CR values above 0.85, which indicates that they are stable and reliable. However, some constructs such as TOL (CR = 0.750) and IMP (CR = 0.759) have Cronbach's Alpha values below 0.6, which suggests that these constructs may need to be further studied or improved by adding more relevant indicators.

The last table, table 6, shows the contribution of each variable that shows an overall result above 0.75 or indicates a strong value.

Table 6. R square

	R square	**R square adjusted**	**Category**
SoM	0.962	0.961	Strong
SoR	0.894	0.893	Strong
ER	0.981	0.981	Strong
RES	0.944	0.943	Strong

3.2. Discussion

This study aims to explore the factors that affect *resilience* in the context of the delay in the distribution of humanitarian logistics, by reviewing three main constructs: *Sense of Mastery (SoM)*, *Sense of Relatedness (SoR)*, and *Emotional Reactivity (ER)*. The *Partial Least Squares Structural Equation Modeling (PLS-SEM)* approach is used to identify the direct and indirect relationship between indicators and key constructs.

The results of the analysis showed that *SoM* had a significant influence on *resilience (RES),* which showed that individuals with high confidence in controlling the situation were more likely to have strong resistance to logistical delays. *SoR* also contributes to *RES*, despite of lower significance than *SoM*. Meanwhile, *ER* showed a negative association with *RES*, indicating that more emotionally reactive individuals tended to have lower levels of resilience in the face of delays in aid distribution.

In the initial model, it can be seen that the indicators in the average COM have poor outer loading values. One possible cause is that respondents in the study were more influenced by other factors such as self-efficacy (SEN) and trust (TRU), which are more associated with confidence in handling delays than emotional comfort. Thus, the decision to remove COM from the model is supported by statistical results that show no significant influence on other variables. This decision is supported by previous research that highlights that self-efficacy and social trust play a greater role in coping with logistical challenges than emotional comfort. For example, research on humanitarian aid workers showed that work stress and individual coping styles had a significant effect on psychological distress and burnout, confirming the importance of self-efficacy in this context (Bakic and Ajdukovic, 2021).

From the direct, indirect, and total effects analysis we can see that in some cases, even though individuals have high levels of emotional resilience, they may still face barriers in maintaining an optimal logistical response. These findings are in line with research that shows that in addition to individual factors, organizational support and community resources also have an important role in post-disaster recovery and adaptation (Bakic and Ajdukovic, 2021).

After removing some weak indicators, the realibility results of the final model show that overall, the reliability of the constructs in the model has been qualified, although some variables require improvements to improve the stability of the measurement (Salisu and Hashim, 2017). Thus, RQA can be used to provide an overview of the resilience of victims of natural disasters due to disaster delays but requires further adjustment because the circumstances of each victim may be different which allows for different outcomes.

Contribution of each variables in the model is also confirmed through strong R-square values for all mediators and endegenous variables with SoM 0.962, SoR 0.894, ER 0.981, and RES: 0.944. These values indicate that the model has excellent predictive capabilities, with more than 90% of the variability in RES explained by SoM, SoR, and ER. It confirms that psychological factors such as confidence in overcoming delays, strong social relationships, as well as the individual's ability to regulate emotional responses play an important role in the logistical resilience of humanity (Bakic and Ajdukovic, 2021).

4.CONCLUSION AND SUGGESTION

The results of this study provide empirical evidence that SoM and SoR significantly contribute to increased resilience, while ER has a negative influence on resilience, suggesting that emotional stability plays an important role in adapting to logistical uncertainties. The findings also confirm that self-efficacy and social support are key factors in building resilience, which can be used to improve aid distribution strategies.

The findings also highlight the importance of strengthening social cohesion and social connectedness to improve individual abilities in dealing with distribution delays. In addition, the negative impact of ER on RES emphasizes the need for psychosocial support mechanisms in humanitarian logistics planning. This insight contributes to the existing literature by integrating the theory of psychological resilience in logistics delay management, providing a multidisciplinary perspective that can be applied in research as well as practice.

By understanding how SoM, SoR, and ER contribute to resilience, this research provides insights for humanitarian organizations and policymakers in designing more adaptive and recipient-centered distribution strategies. Increasing sense of mastery and social connectedness, for example, can be strengthened through disaster preparedness education programs, effective communication during distribution, and building a more solid community to support the psychological resilience of aid recipients.

Furthermore, these findings are expected to be the basis for the development of a more optimal disaster relief distribution network. By considering the psychological aspects of the beneficiaries, the distribution system can be designed to minimize uncertainty and increase the recipient's confidence in the distribution mechanism. In addition, other solutions such as decentralization of distribution centers, optimization of logistics channels, and the use of technology for real-time tracking of aid can be strategic steps to ensure the resilience of disaster victims.

In the future, it is hoped that further research can consider external logistical factors, such as infrastructure conditions, supply chain disruptions, or government policies, which can also affect resilience.

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