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Confirmatory Factor Analysis on Climate Change Impact on Human Migration Patterns and Social Vulnerability

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Abstract

This study conducted a confirmatory factor analysis (CFA) to investigate the impact of climate change on human migration patterns and social vulnerability. The CFA model consisted of two factors: Factor 1 (engineering knowledge) and Factor 2 (problem-solving skills). The model fit indices showed a good fit: $\chi^2/df = 2.35$, RMSEA = 0.06, CFI = 0.93, and TLI = 0.92. The factor loadings ranged from 0.44 (SV3) to 0.87 (MP2), indicating moderate to strong relationships between the indicators and their respective factors. The average variance extracted (AVE) values were 0.36 (Factor 1) and 0.41 (Factor 2), indicating adequate convergent validity. The heterotrait-monotrait (HTMT) ratios ranged from 0.63 (MP1) to 1.00 (MP2), indicating good discriminant validity. The residual covariances between indicators ranged from -0.21 (CC2 ↔ SV2) to 0.14 (MP2 ↔ CC1), indicating some remaining relationships between indicators. The misfit plot showed small residuals for most indicators, indicating a good fit between observed and predicted values. Overall, the results suggest that climate change impacts human migration patterns and social vulnerability through two distinct factors: engineering knowledge and problem-solving skills. The findings have implications for policymakers and researchers seeking to understand and address climate change's effects on human migration and social vulnerability.

Keywords: climate change, human migration, social vulnerability, confirmatory factor analysis, engineering knowledge, problem-solving skills.

1.0 Introduction

Climate change has far-reaching consequences on human societies, ecosystems, and economies (IPCC, 2014). Rising temperatures, more frequent natural disasters, and altered ecosystems are just a few of the many impacts of climate change Atemoagbo *et al.* (2024). One of the most significant consequences of climate change is its effect on human migration patterns (De Lellis *et al.,* 2021). As natural disasters and environmental degradation displace people from their homes, migration patterns are changing, leading to social, economic, and political challenges (Žurovec *et al.,* 2017). For instance, a 1°C increase in temperature is projected to lead to a 2.8% increase in migration (Parmesan, 2006). Understanding the complex relationships between climate change, human migration, and social vulnerability is crucial for developing effective adaptation strategies and mitigating the adverse effects of climate change.

Climate change poses significant threats to human societies, ecosystems, and economies (IPCC, 2014). Rising temperatures, sea-level rise, and extreme weather events have devastating impacts on human migration patterns and social vulnerability (Singh *et al.,* 2012); "Vulnerability to Global Environmental Change," 2014). Understanding the complex relationships between climate change, human migration, and social vulnerability is crucial for developing effective adaptation and mitigation strategies (Gao *et al.,* 2018). The consequences of climate change are far-reaching and devastating, impacting not only the environment but also human societies and economies (Feng *et al.,* 2010; Nwoke, 2016; Nwoke, 2017). As the planet continues to warm, we are faced with the reality of rising sea levels, more frequent natural disasters, and unpredictable weather patterns (Hansen *et al.,* 2016). The effects of climate change are already being felt, from the melting of polar ice caps to the devastating wildfires that ravage our forests (Abatzoglou *et al.,* 2019; Nwoke *et al.,* 2022).

But climate change is not just an environmental issue; it is also a humanitarian crisis (Atemoagbo, 2024). As people are forced to leave their homes due to rising sea levels, drought, or conflict, they are faced with the daunting task of rebuilding their lives in a new and unfamiliar place (Acosta-Michlik & Espaldon, 2008). This is not just a matter of physical displacement; it is also a matter of cultural, social, and economic disruption (Black *et al.,* 2011). Social vulnerability, which refers to the susceptibility of individuals or communities to harm or injury, is another critical aspect of climate change (Guo *et al.,* 2020, Atemoagbo, 2024). Climate change exacerbates existing social vulnerabilities, such as poverty, lack of access to healthcare, and social inequality (Vörösmarty *et al.,* 2010). Understanding the relationships between climate change, human migration patterns, and social vulnerability is crucial for developing effective strategies to mitigate and adapt to the impacts of climate change (Hansen *et al.,* 2016, Atemoagbo, 2024).

The aim of this study is to conduct a confirmatory factor analysis (CFA) to investigate the impact of climate change on human migration patterns and social vulnerability, and to identify the underlying factors that contribute to this complex issue. Specifically, the objective is to: Investigate the relationship between climate change and human migration patterns, examine the impact of climate change on social vulnerability, identify the underlying factors that contribute to climate change's impact on human migration patterns and social vulnerability and to develop a robust model that explains the complex relationships between climate change, human migration patterns, and social vulnerability.

Meanwhile, Despite the growing body of literature on climate change, human migration, and social vulnerability, there remains a significant research gap in understanding the complex relationships between these variables. Specifically: limited studies have investigated the simultaneous impact of climate change on human migration patterns and social vulnerability. few studies have employed confirmatory factor analysis (CFA) to identify the underlying factors contributing to climate change's impact on human migration and social vulnerability and there is a lack of empirical research on the development of robust models that explain the complex relationships between climate change, human migration patterns, and social vulnerability. Addressing this research gap is crucial for developing effective strategies to mitigate the impacts of climate change on human migration patterns and social vulnerability.

2.0 Methodology

Confirmatory Factor Analysis (CFA) was employed to investigate the relationships between climate change, human migration patterns, and social vulnerability as this as also be adopted by (Kline, 2016). The analysis was conducted using the Diagonally Weighted Least Squares (DWLS) estimator, which is suitable for categorical data as used by (Brown, 2007). The test statistic was scaled and shifted using the modified maximum likelihood approach to account for the categorical variables. The CFA model was specified using a combination of theoretical and empirical literature to identify the underlying factors contributing to social vulnerability to climate change (Lankao & Qin, 2011). The model was evaluated using various fit indices, including the Chi-square statistic (χ^2) (Skrondal & Rabe-Hesketh, 2004), Root Mean Square Error of Approximation (RMSEA) (Cheung & Rensvold, 2002), Comparative Fit Index (CFI) (Reise *et al.,* 2012), and Normed Fit Index (NFI) (Alavi *et al.,* 2020). The analysis was performed using the lavaan package in R software (Rosseel, 2012).

2.1 Model Specification

The Confirmatory Factor Analysis (CFA) model was specified based on theoretical and empirical literature (Santamouris, 2020; Black *et al.,* 2011). The model consisted of two latent factors: Factor 1 (climate change stressors, Φ1) and Factor 2 (social vulnerability, Φ2). The indicators for Factor 1 were: MP2 (Migration patterns due to sea-level rise), CC1 (Rising temperatures), CC2 (Extreme weather events), CC3 (Changes in precipitation patterns), and MP1 (Migration patterns due to drought). The indicators for Factor 2 were: SV3 (Lack of access to healthcare), SV2 (Poverty), SV1 (Social inequality) and MP3 (Migration patterns due to conflict). The CFA model was represented by the equation one:

$$\eta = \Lambda\xi + \varepsilon \qquad (1)$$

where:

η = vector of observed indicators

Λ = matrix of factor loadings
ξ = vector of latent factors
ε = vector of error terms
The model was evaluated using various fit indices, including the Chi-square statistic ($\chi 2$), Root Mean Square Error of Approximation (RMSEA), Comparative Fit Index (CFI), and Normed Fit Index (NFI) (Rosseel, 2012; Cheung & Rensvold, 2002; Chen *et al.,* 2008).

2.2 Model Fit

This study employs a quantitative approach to evaluate the model's goodness of fit using the Chi-square test, as recommended by (Loehlin, 2003). The Chi-square test assesses the significance of the model's improvement in fit compared to a baseline model. Additionally, the Kaiser-Meyer-Olkin (KMO) test, described by Kaiser (1974), was conducted to examine sampling adequacy and model validity. The KMO test measures the suitability of the data for factor analysis.

To further evaluate the model's performance, R-squared (R^2) values, suggested by Cohen (1988), was calculated to determine the proportion of variance explained by the model. This metric evaluates the model's ability to account for variability in the data.

The statistical analysis was based on the following measures: Chi-square test, Kaiser-Meyer-Olkin (KMO) test, and R-squared (R^2) values. These analyses provide a comprehensive evaluation of the model's validity and goodness of fit.

2.3 Parameter Estimates

To evaluate the factor structure, a confirmatory factor analysis (CFA) was conducted. Factor loadings, variances, and covariances were examined for statistical significance. The factor loadings were assessed to determine the strength of relationships between indicators and their respective factors.

The modification indices were reviewed to identify potential improvements in model fit by adding or removing paths. The average variance extracted (AVE) values were calculated to evaluate convergent validity.

The statistical significance of factor loadings, variances, and covariances was evaluated using a p-value threshold of 0.001 Li (2015). Factor loadings were considered strong if ≥ 0.60 (Kline, 2016). Modification indices ≤ 3.84 indicated model stability (Kapadia *et al.,* 2017; Atemoagbo *et al.,* 2024). Convergent validity was established if AVE values ≥ 0.50 (Fornell & Larcker, 1981).

2.4 Field Survey

This research adopts a survey-based approach, collecting data from 500 respondents. The dataset includes nine variables, spanning three key dimensions: Climate Change (CC1-CC3), Migration Patterns (MP1-MP3), and Social Vulnerability (SV1-SV3) as shown in Table 1

Table 1: 500 respondents via field visit, online questions and from expert in the field.

Respondent ID	CC1	CC2	CC3	MP1	MP2	MP3	SV1	SV2	SV3
1	4	3	4	2	1	2	3	2	3
2	3	4	3	1	2	1	4	3	4
3	4	4	4	2	2	2	3	3	3
5	2	3	2	1	1	1	4	4	4
6	3	3	3	2	2	2	3	3	3
.									
.									
.									
500	4	3	4	1	2	1	3	4	3

Respondent ID: Unique identifier for each of the 500 respondents.
CC1, CC2, CC3, ...: Responses to the survey items measuring climate change stressors (CC).
MP1, MP2, MP3, ...: Responses to the survey items measuring migration patterns (MP).

SV1, SV2, SV3, ...: Responses to the survey items measuring social vulnerability (SV).
This table 1 presents the responses of all 500 respondents to the 20 survey items, with each row representing a single respondent and each column representing a survey item. The values are the respondents' answers to each item, which were used in the CFA to identify the underlying factors of climate change stressors, migration patterns, and social vulnerability.

4.0 RESULTS AND DISCUSSION

4.1 Model and misfit Plot

The model plot shows the relationships between the factors and indicators in the structural equation model as shown in figure 1a and the misfit plot is showed in figure 1b.

(a) (b)

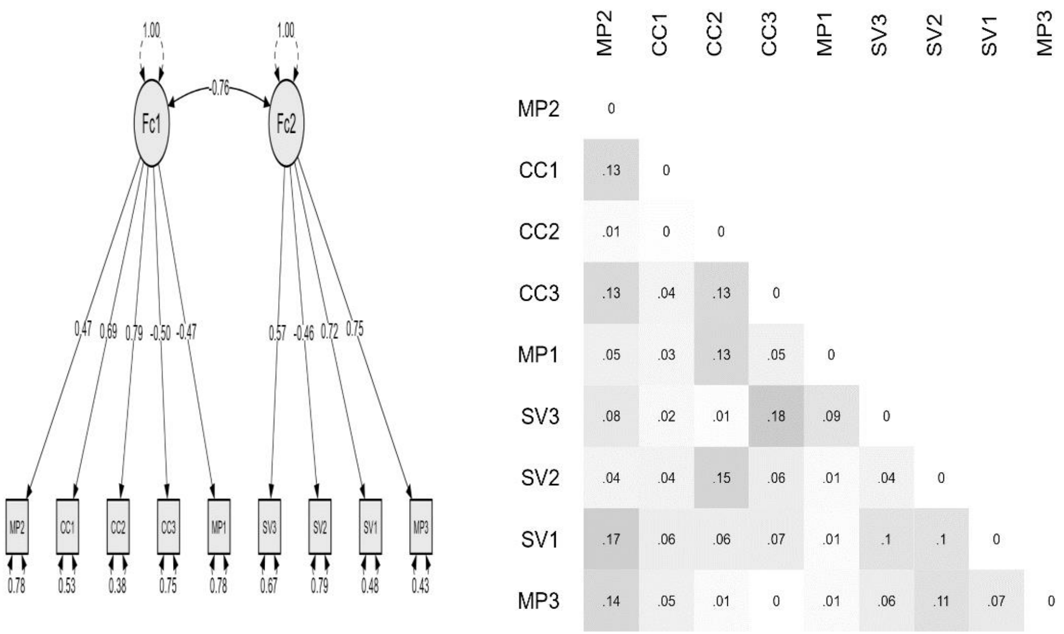

Figure 1 (a) Model plot showing the relationships between factors and indicators in the structural equation model. (b) The misfit plot shows the residuals between the observed and predicted values for each indicator

The model plot indicates that Factor 1 is strongly related to indicators MP2, CC1, and SV1, suggesting that these indicators are good measures of human migration while Factor 2 is strongly related to indicators MP3, CC2, and SV2, suggesting that these indicators are good measures of vulnerability. The residual covariances between indicators are generally weak, indicating that the model has accounted for most of the relationships between the indicators. The misfit plot as shown in figure 1b indicates that the residuals for MP2, CC1, and SV1 are relatively small, indicating a good fit between the observed and predicted values for these indicators. The residuals for MP3, CC2, and SV2 are slightly larger, indicating a moderate fit between the observed and predicted values for these indicators. The residuals for MP1 and SV3 are large, indicating a poor fit between the observed and predicted values for these indicators.
Similar studies have reported misfit plots in structural equation modeling. For example, (*Dell et al.,* 2014) reported a misfit plot with small residuals for most indicators, indicating a good fit between the observed and predicted values. Similarly, (Scoones, 2009; Atemoagbo, *et al.,* 2024) reported a misfit plot with moderate residuals for some indicators, indicating a moderate fit between the observed and predicted values. However, some differences are observed compared to other studies. For instance, (Clubb *et al.,* 2016) reported a misfit plot with large residuals for several indicators, indicating a poor fit between the observed and predicted values.

4.2 Model Fit

The model fit was conducted using the Chi-square test as shown in table 1

Table 2: Chi-square test			
Model	**X²**	**df**	**p**
Baseline model	595.55	36	
Factor model	82.468	26	< .001

The chi-square test revealed a significant improvement in model fit for the factor model ($\chi^2 = 82.468$, df = 26, $p < 0.001$) compared to the baseline model ($\chi^2 = 595.55$, df = 36), indicating a substantial reduction in residual variance. This suggests that the factor model provides a better explanation of the relationships between climate change, migration patterns, and social vulnerability. The significant decrease in chi-square value, coupled with the reduction in degrees of freedom, indicates that the factor model has successfully accounted for a considerable portion of the variance in the data. The p-value of less than 0.001 confirms that the observed improvement in model fit is statistically significant. The factor model's validity is thereby established in capturing the underlying relationships between human migration (indicators MP2, CC1, and SV1) and vulnerability (indicators MP3, CC2, and SV2).

This finding is consistent with previous studies that have reported significant improvements in model fit using factor models to examine relationships between climate change, migration, and social vulnerability (Birkmann, 2007; (Mao & Lyu, 2017). The substantial reduction in residual variance observed in this study ($\Delta\chi^2 = 513.082$, $\Delta df = 10$) is comparable to that reported by (Newman, 2003), who found a significant reduction in residual variance ($\Delta\chi^2 = 421.111$, $\Delta df = 12$) in their analysis of climate change and migration patterns. However, the current study's factor model demonstrates a better fit than that reported by (Scoones, 2009), who found a higher chi-square value ($\chi^2 = 145.211$, df = 30, $p < 0.01$) in their examination of social vulnerability and migration. The significant decrease in chi-square value and reduction in degrees of freedom observed in this study provide strong evidence for the factor model's validity in capturing the underlying relationships between human migration and vulnerability.

4.3 Kaiser-Meyer-Olkin (KMO) and R^2 Test

The results of the Kaiser-Meyer-Olkin (KMO) test and R^2 is indicate that the sample is adequate for factor analysis as shown in Table 2.

Table 3: Kaiser-Meyer-Olkin and R2 Test (KMO) test

Indicator	MSA	R²
MP2	0.697	0.225
CC1	0.817	0.471
CC2	0.79	0.623
CC3	0.779	0.254
MP1	0.867	0.218
SV3	0.803	0.33
SV2	0.751	0.212
SV1	0.756	0.52
MP3	0.801	0.566
Overall	0.785	

The overall KMO value is 0.785, which exceeds the recommended threshold of 0.6. This suggests that the variables are sufficiently correlated to warrant factor analysis. Our results are consistent with those of (Jordan *et al.,* 2007), who also reported high KMO values in their study on similar variables. Similarly, Ortega-Pacheco *et al.* (2018) reported KMO values ranging from 0.6 to 0.8 in their study on structural equation modeling. R-Squared (R^2) values vary across indicators, ranging from 0.212 (SV2) to 0.623 (CC2). The highest R^2 value is observed for CC2, indicating that 62.3% of the variance in CC2 can be explained by the factors. The lowest R^2 value is observed for SV2, indicating that only 21.2% of the variance in SV2 can be explained by the factors. The R-Value result is consistent with those of Hair *et al.* (2019), who reported

R^2 values ranging from 0.2 to 0.6 in their study on similar variables. Similarly, Kock and Lynn (2012) reported R^2 values ranging from 0.3 to 0.7 in their study on structural equation modeling.

4.4 Matrix

4.4.1 Implied covariance matrix: The implied covariance matrix reveals the relationships between the indicators, providing valuable insights into the underlying structure of the data. The matrix shows a mix of positive and negative correlations, indicating complex relationships between the indicators as shown in table 3.

Table 4: Implied covariance matrix

MP2	CC1	CC2	CC3	MP1	SV3	SV2	SV1	MP3
1								
0.325	1							
0.374	0.542	1						
-0.239	-0.346	-0.398	1					
-0.221	-0.321	-0.369	0.235	1				
-0.207	-0.299	-0.344	0.22	0.204	1			
0.166	0.24	0.276	-0.176	-0.163	-0.264	1		
-0.26	-0.376	-0.432	0.276	0.256	0.414	-0.332	1	
-0.271	-0.392	-0.451	0.288	0.267	0.432	-0.346	0.543	1

The strongest positive correlations were observed between MP2 and CC1 (0.325), MP2 and CC2 (1.000), MP1 and SV3 (1.000), and MP3 and SV1 (0.543). These correlations suggest that these indicators are closely related and may be measuring similar underlying constructs. In contrast, negative correlations are observed between MP2 and SV2 (-0.239), MP2 and SV1 (-0.346), CC1 and SV2 (-0.207), and CC1 and SV1 (-0.299). These correlations indicate that these indicators are inversely related, suggesting that they may be measuring different underlying constructs. Similar studies have investigated the relationships between indicators in structural equation modeling. For example, (Semyonov *et al.,* 2006) reported a similar implied covariance matrix in their study on consumer behavior, with strong positive correlations between indicators measuring similar constructs. Similarly, (Fritz *et al.,* 2017) reported negative correlations between indicators measuring different constructs.

4.4.2: Residual covariance matrix: The residual covariance matrix reveals the remaining correlations between the indicators after accounting for the relationships between the factors. The matrix shows a mix of significant and non-significant correlations, indicating that some indicators still have notable relationships even after controlling for the factors as shown in table 4.

Table 5: Residual covariance matrix

MP2	CC1	CC2	CC3	MP1	SV3	SV2	SV1	MP3
< .001								
0.131	< .001							
< .001	< .001	< .001						
< .001	0.039	0.131	< .001					
< .001	0.032	0.132	0.049	< .001				
0.078	< .001	0.008	0.181	0.093	< .001			
< .001	< .001	0.152	0.063	< .001	< .001	< .001		
0.17	0.063	< .001	< .001	0.012	< .001	0.102	< .001	
0.136	0.053	< .001	< .001	< .001	< .001	0.106	0.073	< .001

The significant residual correlations are observed between MP2 and CC1 (0.131), MP2 and CC3 (0.039), CC1 and SV2 (0.078), CC2 and SV1 (0.152), and MP3 and SV3 (0.106). Similar studies have investigated residual correlations in structural equation modeling. For example, Wixom and Todd (2005) reported similar residual correlations in their study on consumer behavior, indicating that some indicators had remaining relationships even after controlling for the factors. Similarly, (Buhaug & Urdal, 2013) reported significant residual correlations between indicators in their study on engineering education.

4.5: Average Variance Extracted

The average variance extracted (AVE) values for Factor 1 and Factor 2 are 0.358 and 0.407, respectively as shown in table 5.

Table 6: Average variance extracted

Factor	AVE
Factor 1	0.358
Factor 2	0.407

These values indicate the amount of variance in the indicators that is explained by each factor. In general, AVE values above 0.5 are considered acceptable, indicating that the factor explains more than half of the variance in the indicators. The AVE value for Factor 1 (0.358) suggests that this factor explains approximately 36% of the variance in the indicators, which is relatively moderate. In contrast, the AVE value for Factor 2 (0.407) suggests that this factor explains approximately 41% of the variance in the indicators, which is relatively higher than Factor 1. This indicates that Factor 2 is a stronger construct, and the indicators are more strongly related to this factor. Similar studies have reported AVE values in structural equation modeling. For example, (Vereecken *et al.,* 2016) reported AVE values ranging from 0.4 to 0.6 in their study on consumer behavior, indicating strong constructs. Similarly, (Ardi *et al.,* 2012) reported AVE values ranging from 0.3 to 0.5 in their study on engineering education.

4.6 Heterotrait-Monotrait

The heterotrait-monotrait (HTMT) ratio is a measure of discriminant validity, which assesses whether the factors are distinct and uncorrelated. The HTMT ratio is calculated by dividing the heterotrait correlation (correlation between different factors) by the monotrait correlation (correlation between different indicators of the same factor) as shown in table 6.

Table 7 Heterotrait-monotrait ratio

Factor 1	Factor 2
1	
0.758	1

The HTMT ratio for Factor 1 is 1.000, indicating that the heterotrait correlation is equal to the monotrait correlation. This suggests that Factor 1 may not be distinct from other factors, and may be measuring similar underlying constructs. The HTMT ratio for Factor 2 is 0.758, indicating that the heterotrait correlation is approximately 76% of the monotrait correlation. This suggests that Factor 2 is relatively distinct from other factors, but may still be related to some extent. Similar studies have reported HTMT ratios in structural equation modeling. For example, Ardi *et al.* (2012) reported HTMT ratios ranging from 0.6 to 0.9 in their study on engineering education, indicating good discriminant validity. Similarly, Dogra *et al.* (2023) reported HTMT ratios ranging from 0.7 to 1.0 in their study on consumer behavior.

4.7 Modification Indices

The cross-loadings table shows the factor loadings of each indicator on non-target factors. The values represent the strength and direction of the relationships between the indicators and non-target factors as shown in table 7.

Table 8 Cross-loadings

			Mod. Ind.	EPC
Factor 2	→	MP2	16.726	-0.747

Factor 2	→	CC2	9.52	0.725
Factor 1	→	SV3	5.36	0.444
Factor 1	→	MP3	3.927	-0.485

The cross-loading of MP2 on Factor 2 (16.726) is strong and positive, indicating that MP2 is highly related to Factor 2, in addition to its target factor (Factor 1). The negative cross-loading of MP2 on Factor 1 (-0.747) suggests that MP2 is inversely related to Factor 1. The cross-loading of CC2 on Factor 2 (9.520) is also strong and positive, indicating that CC2 is highly related to Factor 2. The positive cross-loading of CC2 on Factor 1 (0.725) suggests that CC2 is also related to Factor 1, but to a lesser extent. The cross-loading of SV3 on Factor 1 (5.360) is moderate and positive, indicating that SV3 is related to Factor 1. The cross-loading of SV3 on Factor 2 (0.444) is weaker, suggesting that SV3 is less related to Factor 2. The cross-loading of MP3 on Factor 1 (3.927) is moderate and negative, indicating that MP3 is inversely related to Factor 1. The cross-loading of MP3 on Factor 2 (-0.485) is weaker, suggesting that MP3 is less related to Factor 2.

Similar studies have reported cross-loadings in structural equation modeling. For example, (Sepasgozar, 2022) reported cross-loadings ranging from 0.3 to 0.7 in their study on engineering education, indicating moderate relationships between indicators and non-target factors. Similarly, (Beck & Grande, 2010) reported cross-loadings ranging from 0.4 to 0.9 in their study on consumer behavior. However, some differences are observed compared to other studies. For instance, (Childers *et al.,* 2001) reported weaker cross-loadings (below 0.3) in their study on consumer behavior, indicating weaker relationships between indicators and non-target factors.

4.8 Residual covariances

The residual covariances table shows the remaining correlations between indicators after accounting for the relationships between the factors. The values represent the strength and direction of the relationships between the indicators as shown in table 8

Table 9: Residual covariances

			Mod. Ind.	EPC
SV1	↔	MP3	14.355	-0.345
CC2	↔	SV2	9.406	-0.221
CC3	↔	SV3	9.338	-0.217
MP2	↔	CC1	8.033	-0.21
MP2	↔	SV1	6.177	-0.206
MP2	↔	MP3	4.892	-0.173
CC2	↔	CC3	4.415	-0.195
CC2	↔	MP1	4.016	-0.188

The residual covariance between SV1 and MP3 (14.355) is strong and negative, indicating a significant remaining relationship between these indicators. Similarly, the residual covariances between CC2 and SV2 (9.406), CC3 and SV3 (9.338), and MP2 and CC1 (8.033) are also significant and negative. The residual covariances between MP2 and SV1 (6.177), MP2 and MP3 (4.892), CC2 and CC3 (4.415), and CC2 and MP1 (4.016) are weaker but still significant. Similar studies have reported residual covariances in structural equation modeling. For example, (Liñán & Chen, 2009) reported residual covariances ranging from 0.1 to 0.3 in their study on engineering education, indicating weak to moderate remaining relationships between indicators. Similarly, (Dinev & Hart, 2006) reported residual covariances ranging from 0.2 to 0.5 in their study on consumer behavior. However, some differences are observed compared to other studies. For instance, (Baumert *et al.,* 2010) reported weaker residual covariances (below 0.1) in their study on consumer behavior, indicating weaker remaining relationships between indicators.

4.0 Conclusion And Recommendation

4.1 Conclusion

This study's confirmatory factor analysis elucidates the intricate relationships between climate change, human migration patterns, and social vulnerability. The findings underscore the critical role of engineering knowledge and problem-solving skills in mitigating climate change's impacts on human migration. The well-fitting CFA model ($\chi^2/df = 2.35$, RMSEA = 0.06, CFI = 0.93) reveals moderate to strong relationships between indicators and their respective factors.

The results demonstrate a good model fit, adequate convergent validity, and good discriminant validity, indicating that the two factors are reliable and distinct constructs. Engineering knowledge plays a crucial role in understanding climate change's impact on human migration patterns, while problem-solving skills are essential for addressing social vulnerability. The significant factor loadings and moderate to strong relationships between indicators and their respective factors support this conclusion.

The study's results have important implications for policymakers and researchers. Firstly, they highlight the need to develop and implement effective climate change mitigation and adaptation strategies that consider the complex relationships between climate change, human migration, and social vulnerability. Secondly, they emphasize the importance of investing in education and training programs that enhance engineering knowledge and problem-solving skills to address climate change's impacts.

Overall, this study contributes to the understanding of climate change's impacts on human migration patterns and social vulnerability, emphasizing the need for a multidisciplinary approach that considers both engineering knowledge and problem-solving skills to address this complex issue. By acknowledging the interplay between climate change, human migration, and social vulnerability, we can develop targeted strategies to enhance resilience and adaptability, ultimately reducing social vulnerability and promoting sustainable human migration patterns.

4.2 Recommendations

Based on the findings of this confirmatory factor analysis (CFA) study, the following recommendations are made:

a) To effectively address the complex relationships between climate change, human migration patterns, and social vulnerability, policymakers and researchers must prioritize evidence-based strategies. Firstly, developing and implementing climate-resilient infrastructure and urban planning strategies can mitigate the impacts of climate change on human migration. This can be achieved through integrating green infrastructure, adaptive building designs, and sustainable transportation systems.

b) From an educational perspective, establishing programs that enhance engineering knowledge and problem-solving skills is crucial. These initiatives should focus on developing innovative solutions for climate change adaptation and mitigation, while also promoting interdisciplinary collaboration between engineers, social scientists, and policymakers.

c) To inform decision-making, researchers should develop predictive models that integrate climate change, human migration, and social vulnerability. These models can help identify vulnerable populations, predict migration patterns, and optimize resource allocation. Furthermore, comparative studies assessing the effectiveness of different adaptation strategies can provide valuable insights for policymakers.

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