INVESTIGATING THE VENEZUELAN HUMANITARIAN AND MIGRATORY CRISIS: AN FMEA AND ETA ANALYSIS VIA MULTIPLE REGRESSION

INVESTIGANDO A CRISE HUMANITÁRIA E MIGRATÓRIA VENEZUELANA: UMA ANÁLISE DE FMEA E ETA VIA REGRESSÃO MÚLTIPLA

INVESTIGANDO LA CRISIS HUMANITARIA Y MIGRATORIA VENEZOLANA: UN ANÁLISIS DE FMEA Y ETA MEDIANTE REGRESIÓN MÚLTIPLE

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Daniel Francisco Scolaro Cordeiro[1], Thyago Henrique Teixeira de Sousa[2], Ivan Augusto Cecilio e Silva[3]

ABSTRACT

This article addresses the migratory and humanitarian crisis in Venezuela, focusing on the analysis of the economic and social roots of this complex phenomenon. To comprehensively understand and approach the crisis, the Failure Mode and Effects Analysis (FMEA) and Event Tree Analysis (ETA) methodologies were applied, with results compared to those generated by two Artificial Intelligences (AI): Google Bard and ChatGPT. Additionally, the study employed a robust multiple regression econometric model to investigate the impact of socioeconomic variables on Venezuelan net migration from 1998 to 2022. The findings revealed that factors such as inflation, gross debt, oil production, and mortality rate played significant roles in the observed mass migration. These conclusions are essential for understanding the underlying economic dynamics of the crisis and may contribute to the development of more effective and sustainable policies to address it.

Keywords: Migration. Venezuela. Inflation. Artificial Intelligence. FMEA.

RESUMO

Este artigo aborda a crise migratória e humanitária na Venezuela, com foco na análise das raízes econômicas e sociais desse fenômeno complexo. Para entender e abordar a crise de maneira abrangente, foram aplicadas a Análise de Modo e Efeito de Falha (FMEA) e a Análise de Árvore de Eventos (ETA), com resultados comparáveis ao de duas Inteligências Artificiais (IA), o Google Bard e o Chat GPT. Adicionalmente, o artigo empregou um modelo econométrico de regressão múltipla robusto para investigar o impacto das variáveis socioeconômicas na migração líquida venezuelana ao longo do período de 1998 a 2022. Os resultados revelaram

[1] Master's degree in Applied Economics. Universidade Federal do Rio Grande do Sul (PPGE/UFRGS).
E-mail: danielfrancisco2000@gmail.com Orcid: https://orcid.org/0009-0002-2366-7134
Lattes: 5098730445330720
[2] Master's degree in Applied Economics. Universidade Federal do Rio Grande do Sul (PPGE/UFRGS).
E-mail: thyago.sousa@ufrgs.br Orcid: https://orcid.org/0009-0004-6342-5660
Lattes: 5414958832933420
[3] Master's degree in Applied Economics. Universidade Federal do Rio Grande do Sul (PPGE/UFRGS).
E-mail: ivanaugustocs@gmail.com Orcid: https://orcid.org/0000-0001-9310-1633
Lattes: 0617219530177722

que fatores como inflação, dívida bruta, produção petrolífera e taxa de mortalidade desempenharam papéis significativos na migração em massa observada. Essas conclusões são essenciais para a compreensão das dinâmicas econômicas subjacentes à crise e podem contribuir para o desenvolvimento de políticas mais eficazes e sustentáveis para enfrentá-la.

Palavras-chave: Migração. Venezuela. Inflação. Inteligência Artificial. FMEA.

RESUMEN

Este artículo aborda la crisis migratoria y humanitaria en Venezuela, con foco en el análisis de las raíces económicas y sociales de este fenómeno complejo. Para comprender y abordar la crisis de manera integral, se aplicaron el Análisis de Modo y Efecto de Falla (FMEA) y el Análisis de Árbol de Eventos (ETA), con resultados comparables a los de dos inteligencias artificiales (IA), Google Bard y ChatGPT. Además, el artículo empleó un modelo econométrico robusto de regresión múltiple para investigar el impacto de variables socioeconómicas en la migración neta venezolana en el período de 1998 a 2022. Los resultados revelaron que factores como la inflación, la deuda bruta, la producción petrolera y la tasa de mortalidad desempeñaron papeles significativos en la migración masiva observada. Estas conclusiones son esenciales para entender las dinámicas económicas subyacentes a la crisis y pueden contribuir al desarrollo de políticas más eficaces y sostenibles para enfrentarla.

Palabras clave: Migración. Venezuela. Inflación. Inteligencia Artificial. FMEA.

1 INTRODUCTION

Historical accounts indicate that Venezuela's oil industry took off in the 1920s, after landmark discoveries, spurring investment in infrastructure and public services (Roy & Cheatham, 2024). Venezuela holds the world's largest proven fossil fuel reserves, according to OPEC's Annual Statistical Bulletin, the county held about 303.6 billion barrels of proved crude reserves at end-2020 (OPEC, 2021). Oil exports have been the main source of income for decades, and both production and prices have had a decisive impact on the nation's economy, directly influencing national income and the government's capacity to provide basic public services, as discussed by Kleszczyńska (2020).

Venezuela's export earnings have historically been overwhelmingly oil-dependent, with oil accounting for well over 90% of merchandise exports in many periods (Roy & Cheatham, 2024). The present study indicates that the main factors leading to the crisis began in 2014, when the price of oil dropped sharply in the international market from around US$100 to less than US$40 by the end of 2015, as reported by the U.S. Energy Information Administration (EIA, 2016). Crespo and Zambrano (2018) explain that this price shock had a strong impact on the Venezuelan economy, reducing government revenues and compromising the budget for social programs that benefited a large share of the population. The outcome was a deep recession, reflected in the fall of GDP, hyperinflation, shortages of food and medicine, rising poverty and violence, and declining oil production. Vera (2015) analyzes macro-policy and oil governance over 1999–2014, highlighting institutional and policy vulnerabilities that predated and later amplified the downturn.

According to Tapia et al. (2022), the Venezuelan economy began to experience one of the sharpest declines ever recorded in peacetime, marking a serious humanitarian crisis. This process of deterioration has advanced rapidly, leading the country into political, economic, and social collapse, as observed by Venezuelan and Ausman (2019). In this context, millions of Venezuelans decided to leave the country in search of better living conditions. More than 7.1 million people emigrated from Venezuela between the years 2015 and 2023 (R4V, 2023).

This research project aims to conduct a detailed analysis of the systemic crisis currently affecting Venezuela and its economic impacts, which distort national institutions and lead to serious social issues such as extreme poverty, poor sanitary conditions, and a rapid increase in violence. The central hypothesis of this study is that the combined effects of these factors create a situation of extreme vulnerability for most Venezuelans. In conditions of severe poverty, individuals struggle to access food, healthcare, education, and economic opportunities, which drives them to migrate in search of better living standards.

Based on the principle of economic rationality proposed by Varian (1978), rational individuals are understood to make decisions after carefully evaluating the costs and benefits of their choices. In the context of migration, these individuals compare the opportunities available in their home country with those elsewhere. When external options offer better living conditions, migration becomes a rational decision, as pointed out by Stahl (1983). Addressing the economic principles relevant to migration decisions and based on the literature review, contextualizing the current Venezuelan scenario will serve as the starting point for building a qualitative strand. This approach is intended to justify the research direction, given that the object of study concerns the largest population exodus in Latin American history and one of the major humanitarian crises of the twenty-first century, comparable only to the poorest countries of Sub-Saharan Africa and to Middle Eastern countries in armed conflict such as Syria, Yemen, and Sudan. Mu and Hu (2018) examined the efficiency and stability of the Venezuelan economy and argued that three factors heightened uncertainty about the country: (1) an extreme dependence on the oil industry as the sole wealth-generating sector; (2) an inefficient regulatory system; and (3) slow and unresponsive reactions to external changes.

In selecting a model, the principle of parsimony will be followed, seeking the smallest number of parameters that adequately represent the time series. This principle, attributed to Burnham and Anderson (2002) is commonly interpreted as simpler models fit comparably well against overspecified models. Building a robust model to forecast Venezuela's net population flows will therefore require calibration to obtain the best estimates of known parameters. Complex phenomena demand sophisticated analysis grounded in solid evidence while also adhering to caution and moderation in the use of data and tools; this is not a trivial task. Nevertheless, given the social and humanitarian relevance of the topic, and considering that the databases come from official sources and are open source, this article aims to construct an econometric regression model in Python and compare its outputs with the results obtained by data processing using Artificial Intelligences (AI) such as Google Bard and ChatGPT-4, whose codebases operate as black boxes, both supported by GitHub Copilot.

Constructing a robust multiple regression econometric model with covariates selected from the academic literature and implemented in Python to process data for the period 1998–2022 can simultaneously satisfy two risk analysis and mitigation frameworks: Failure Mode and Effects Analysis (FMEA) and Event Tree Analysis (ETA), as discussed by the International Organization for Standardization (ISO, 2019). This approach can provide the model with sufficient computational capability to handle cutting-edge data when compared with current standards, given that AIs are an advanced tool when synchronized with a copilot, that can access the internet, perform keyword- and topic-based searches, analyze databases, and optimize outputs while formulating responses.

This study is organized as follows, in addition to this Introduction. Section 2 presents a literature review on the determinants of migration within Venezuela's oil-dependent economy. Section 3 details the empirical methodology used for specifying the econometric model. Section 4 reports the main findings and analyzes the results. Finally, Section 5 offers the concluding remarks.

2 THEORETICAL FRAMEWORK

The reasons for migration from one country to another are diverse and may include economic motives, such as the search for better job opportunities, geographic proximity, and economic stability; social reasons, such as reuniting with family members and obtaining access to quality services; political motives, such as escaping persecution and seeking political and personal stability; in addition to the pursuit of cultural and personal experiences, as Castelli (2018) explains.

To explain the drivers of emigration for a Venezuelan citizen, the Refugee and Migrant Needs Analysis (RMNA) was developed by the Regional Inter-Agency Coordination Platform for Refugees and Migrants from Venezuela (R4V). According to R4V (2023), Venezuelan migrants sought destinations that offered safer places, opportunities to obtain income, and access to basic services. This is because the country faces a series of economic conditions that undermine the population's well-being, such as product shortages, hyperinflation, political instability, and violence, as noted by Castro (2020).

Given this scenario, R4V (2023) reports that more than 7.1 million emigrants left Venezuela between 2015 and 2023, with more than 80% hosted in 17 countries in Latin America and the Caribbean. However, the International Organization for Migration (IOM, 2020) indicates that these individuals have heterogeneous socioeconomic profiles and intentions when settling in host countries. IOM (2020) also observes that Venezuelans who move to neighboring countries (for example, Brazil and Colombia) are younger and have relatively lower levels of education and access to health care compared to Venezuelans who moved to more distant countries, where half have some level of higher education (for example, Argentina, Chile, Costa Rica, and Uruguay). Considering this, IOM (2020) concludes that there is a tendency for migrants with higher technical qualifications to move farther from their country of origin.

Nevertheless, within host countries refugees face several setbacks. As the report from R4V (2023) indicates, approximately 50% of Venezuelan migrants present in Latin America and the Caribbean face difficulties in accessing food, education, health care and stable employment. In addition to documentation barriers, R4V (2023) points out that low wages further complicate Venezuelans capacity for subsistence. Despite these challenges, IOM (2020) notes that approximately 80% of these individuals intend to remain where they are, as they consider this to be the best decision for their own and their families well-being. To understand the scenario that generated this mass exodus from Venezuela, it is worth contextualizing the importance of oil to this economy.

2.1 RELATIONSHIP BETWEEN THE VENEZUELAN ECONOMY AND WEALTH VIA OIL

The importance of oil to the world is undeniable, as it is a fundamental energy source for many countries. According to OPEC's Annual Statistical Bulletin (2021), Venezuela holds the world's largest proved crude oil reserves, and export profiles show that oil has historically dominated the country's merchandise exports. Kleszczyńska (2020) notes that production and the international price of this asset directly affect national income and local economic performance. However, excessive dependence on oil can have negative consequences.

The Dutch disease is an economic phenomenon that arises when a country experiences a boom in a natural resource sector, which leads to an artificial appreciation of the domestic currency, taking a heavy dependence on the extractive sector due to strong international demand. Corden and Neary (1982) coined the term in response to the decline of manufacturing and the rise in unemployment in the Netherlands in the 1970s after the discovery of oil and gas in the North Sea. This phenomenon comprises two main effects: the spending effect and the resource-movement effect, as described by Fardmanesh (1991). The first occurs when rising natural resource prices initially trigger a real appreciation that increases the profitability of the appreciated export; this price increase can drive currency appreciation and harm the competitiveness of tradable sectors unrelated to natural resources. According to Corden and Neary (1982), the resource-movement effect draws labor and capital toward the booming resource and non-tradable sectors, squeezing other tradable activities.

In the Venezuelan context, an economy highly dependent on income from fossil fuel exports. Fardmanesh (1991) observes that a sharp rise in oil prices harms tradable sectors such as manufacturing and agriculture, depressing their output in favor of the expanding oil market. Kulkarni and Nicholson (2010) further report a high and significant correlation between Venezuela's dollar reserves, money supply, and inflation. Costa and Olivo (2008) find that money growth and government spending in oil-exporting countries are highly correlated with the commodity's price; thus, the terms-of-trade gain is tied especially to price and less to exported volume. For petrostates operating under government-managed fixed exchange rates, interventions to hold the peg during positive oil-price shocks can be expansionary in monetary terms, as discussed by Mercedes da Costa (2008). As a result, the domestic market becomes more exposed to price fluctuations, culminating in high inflation.

As these effects unfold, exports from non-oil sectors decline. In the domestic market, consumers can import cheaper goods that other countries produce with comparative advantage, further deepening the decline of sectors unrelated to the appreciated commodity. Wang (2022) summarizes that there is a general deterioration in the terms of trade: production becomes lower than it originally was in markets unrelated to the natural resource, while it becomes relatively higher for the good linked to the disease. In Venezuela, Vidal and Mazzali (2019) note that more than 70% of food is imported and that domestic pharmaceutical production is practically nonexistent. Consequently, sectors essential for population well-being become dependent on foreign policy.

Over the last decade, this dependence was further strained by successive sanctions imposed on the Venezuelan government. The U.S. Department of the Treasury (2023) reports that, after the United States deemed Venezuela a national security threat in 2015, sanctions were applied to Venezuelan officials and, in 2017, new debt, shares, and bonds issued by the Venezuelan government and its state-owned companies were barred from U.S. financial markets. In 2019, an economic embargo froze all Venezuelan government property and assets in the United States, including those of the Central Bank of Venezuela. Gratius (2021) explains that these measures aimed to block Venezuela's international trade and curb its ability to raise funds abroad.

The most evident effects of the sanctions were declines in trade, foreign investment, and development assistance. The European Commission (2019) indicates that limited trade relations between Venezuela and the European Union drove exports down from €6.5 billion in 2012 to €0.69 billion in 2019, while imports were reduced by approximately 50% over the same period. In the United States, the U.S. Census Bureau (2019) reports that Venezuelan exports fell from $38.7 billion to $1.9 billion in 2019.

When external markets are restricted and the state has fewer resources, importing food, medicines, and other essential supplies becomes even more difficult. Moreover, constraints on the oil industry's trade affect the core of an economy already suffering from Dutch disease. As the international price of commodities drops significantly, the economic and humanitarian crisis deepens gradually. Human Rights Watch (2019) observes that, despite the country's wealth in a resource with strong global demand, the population faces high inflation and shortages of basic goods, conditions that can motivate migration.

3 METHODOLOGY

3.1 FAILURE MODE AND EFFECTS ANALYSIS AND EVENT TREE ANALYSIS

Failure Mode and Effects Analysis is a systematic technique used across fields such as engineering, manufacturing, and economics to identify and mitigate potential risks. As described by Cristea and Constantinescu (2017), FMEA rates severity, occurrence, and detectability on 1–10 ordinal scales before computing the Risk Priority Number (RPN). The RPN is calculated for each failure mode to rank and prioritize the identified failure modes. The formula for calculating the RPN is presented by McDermott et al. (2009):

$$RPN = Severity\ (S) \times Occurrence\ (O) \times Detectability\ (D) \qquad (1)$$

Severity (S) represents the magnitude of the impact or consequence if the failure mode occurs. Thus, 1 is the lowest rating, and 10 indicates very high severity, when a potential failure mode affects the safe operation of the system without warning. Occurrence (O) indicates the likelihood that the failure mode will occur; 1 reflects virtually no chance of occurrence and 10 reflects a very high probability with failure being nearly inevitable. Detectability (D) refers to the ability to identify the failure mode before it causes significant impacts; 1 indicates the greatest detection potential, and 10 represents complete uncertainty.

The result of the RPN calculation ranges from 1 to 1000. Higher-RPN failure modes indicate greater risk and require more attention and action to reduce their probability of occurrence or minimize their consequences, as emphasized by McDermott et al. (2009). Addressing social and economic crises requires identifying critical factors that contribute to instability, such as inflation rates, unemployment rates, and fiscal policies. In addition, analyzing the probability of political unrest, corruption, and social tensions can help clarify what exacerbates the crisis. In the context of the Venezuelan migration crisis, FMEA can be applied to identify failure modes associated with its main causes, such as economic crisis, political instability, and lack of access to essential resources. By decomposing the problem into individual failure modes and evaluating their impact, decision-makers can gain a deeper understanding of the underlying causes and vulnerabilities that contribute to the crisis.

On the other hand, complementing FMEA with another risk analysis technique, such as Event Tree Analysis, can offer a more comprehensive understanding of the crisis. ETA allows modeling complex scenarios and calculating probabilities for spontaneous events, as discussed explained by Fernandes, Cristina, and Filho (2022). Its tree-like structure facilitates the visualization and understanding of possible paths that lead to an outcome. For example: let A be an external event (final event) for which we want to analyze possible causes and consequences, the probability of event A occurring, $P(A)$, can be seen using the ETA formula:

$$P(A) = \sum_i P(B_i)\, P(A \mid B_i), \qquad (2)$$

Where:

$\{B_i\}$ denotes a mutually exclusive and exhaustive set of initiating scenarios; accordingly, $P(B_i)$ is the probability of scenario B_i, and $P(A \mid B_i)$ is the conditional probability of the outcome given that scenario (Ross, 2019).

In event tree analysis, according to ISO (2019), the probability of a given outcome is obtained by multiplying branch probabilities along each path to that outcome and then summing across relevant paths.

In sum, combining FMEA and ETA offers complementary perspectives on failure modes and consequence pathways, as outlined in ISO (2019) and illustrated in applied risk studies such as Fernandes et al. (2022). Conducting a multiple regression analysis technique capable of simultaneously satisfying an FMEA and an ETA constitutes a sophisticated tool used to control the effect of confounding variables in economic models. These variables can influence outcomes and lead to spurious relationships between independent and dependent variables, causing biased or incorrect results, as highlighted by Cristea and Constantinescu (2017). According to Wooldridge (2013) and Hernán and Robins (2020), multiple regression and doubly robust estimators address confounding in observational data as a separate statistical layer that can complement, but does not substitute, qualitative or semiquantitative risk analyses. Thus, both exposure models and outcome models can be adjusted, leading to more accurate estimates of the effects of the variables of interest.

3.2 ECONOMETRIC MODEL SPECIFICATION

When considering the complex nature of economic data and following the principle of parsimony, we employ a robust regression approach to mitigate potential deviations from classical assumptions. As described by Huber (1981), we estimate a robust M-estimator via IRLS with the Huber loss, and we compute heteroskedasticity-consistent standard errors using the HC1 (Huber–White) sandwich covariance based on White (1980). The robust regression expressed below enables efficient analysis of the impact of macroeconomic factors on Venezuelan net migration. The adopted specification is:

$$net\_migration = \beta_0 + \beta_1 \times inflation + \beta_2 \times gross\_debt + \beta_3 \times mortality + \beta_4 \times oil\_production + \beta_5 \times youth\_employment + \beta_6 \times hunger + \beta_7 \times primary\_enrollment + \beta_8 \times oil\_price + \varepsilon, \quad (3)$$

Where:

β_0 is the intercept, β_i with $i = 1, \dots, 8$ represents the coefficients of the explanatory variables, and ε is the random error term. Table 1 presents the regression variables, data sources, quantitative scale, and the transformation method used to achieve stationarity.

Table 1

Presentation of the variables studied for Venezuela

Variable	**Description**	**Transformation Method for Stationarity**	**Source and Code Series**
Net_migration	Dependent variable of the model: number of immigrants (people entering a given country) minus the number of emigrants (people leaving the country).	Differencing, order 3; KNN imputation	(World Bank, 2023, WDI SM.POP.NETM)
inflation	Inflation rate, consumer prices at end of period (annual percentage change).	Differencing, order 8; KNN imputation; Differencing, order 1; KNN imputation	(IMF, 2023, WEO—CPI)
gross_debt	Gross public sector debt (% of GDP).	Differencing, order 2; KNN imputation; Smoothing	(IMF, 2023, WEO—GGXWDG_NGDP)
mortality	Mortality rate (deaths per 1,000 people).	Differencing, order 4; KNN imputation; Smoothing; Logarithm	(World Bank, 2023, WDI SP.DYN.CDRT.IN)
oil_production	Total oil production (million barrels per day, annual average).	Differencing, order 1; KNN imputation	(EIA, 2023—crude oil

			production)
youth_employment	Labor force participation rate (% of population aged 15 to 24).	None	(World Bank, 2023, WDI SL.TLF.1524.ZS)
hunger	Hunger statistics (% of the population).	None	(FAO, 2023, FAOSTAT—POU)
primary_enrollment	School enrollment rate at the primary level (%).	Differencing, order 1; KNN imputation	(World Bank, 2023, WDI SE.PRM.NENR)
oil_price	End-of-period oil price (US$).	Logarithm; Differencing, order 1; KNN imputation	(EIA, 2023—Europe Brent spot price)

Stationarity is fundamental for time-series regression, to achieve this, three methods are employed. First, differencing consists of subtracting previous values of the series, resulting in a series of differences; the order of differencing determines how many past steps are subtracted. Second, smoothing uses techniques such as moving averages to reduce random variation and highlight long-term patterns. Third, the natural logarithm (ln) is applied to stabilize variance in series with exponential growth, making them more suitable for analysis. As described by Batista and Monard (2003), the KNN imputation method fills gaps due to missing data using values observed nearby in time, which compensates for the loss of observations during differencing. As noted by Box et al. (2016) these transformations make the series more suitable for econometric modeling and forecasting.

4 RESULTS

This section presents the results of the robust regression model used to investigate the determinants of net migration in an economic context. The model was fitted with data collected over the period 1998 to 2022, with the aim of understanding how macroeconomic variables influence population migration from Venezuela.

Table 2 displays the results of eight specifications of economic models obtained through an iterative procedure. Initially, all variables under study were included in model (1). In each subsequent iteration, the variable with the lowest level of significance (p-value) was removed, until only one significant variable remained in the final model (8). This selection process sought to identify the most parsimonious and statistically relevant configuration for the economic analysis in question. Among the specifications presented, model (5) and model (7) deserve emphasis. In model (5), four variables proved statistically significant, contributing to the explanation of 61.75% of the variation in net migration. In model (7), two variables were statistically significant and explained 43.97% of the observed variation in net migration.

Table 2

Results of robust regression models, 1998 to 2022 (n = 25)

Model	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
R^2	0,6627	0,6579	0,6413	0,6427	0,6175	0,5279	0,4397	0,3026
constant	-247.500 (575.000)	-287.000 (531.000)	-396.400 (478.000)	-517.400 (418.000)	154.900* (85.100)	115.700 (48.400)	7998 (13.500)	-118 (739)
inflation	0,0608*** (0,014)	0,0592*** (0,013)	0,0615*** (0,012)	0,0604*** (0,012)	0,0674*** (0,010)	0,0649*** (0,006)	0,0626*** (0,003)	0,0524*** (0,000)
gross_debt	-12.530*** (3.590)	-13.320*** (3.086)	-12.910*** (2.929)	-12.370*** (2.830)	-11.380*** (2.617)	-8.949*** (1.421)	-6612*** (891)	
mortality	-4.036.000* (2.080.000)	-3.980.000** (1.920.000)	-4.046.000** (1.820.000)	-3.788.000** (1.760.000)	-3.907.000** (1.620.000)	-2.454.000*** (928.000)		
oil_production	-602.300** (279.000)	-557.400** (239.000)	-481.900** (225.000)	-440.100** (209.000)	-348.900** (175.000)			
youth_employment	10.750 (12.200)	11.670 (11.200)	14.060 (10.100)	15.490 (9.419)				
hunger	-7.638 (8.309)	-6.826 (7.522)	-4.969 (6.653)					
primary_enrollment	26.790 (36.200)	26.530 (33.700)						
oil_price	63.500 (135.000)							

Note: Standard error in parentheses; *** p-value < 0.01, ** p-value < 0.05, * p-value < 0.1.

Model (5) provides coefficient estimates indicating the effect of the independent variables on net migration while holding the others constant. The constant suggests that, when all independent variables are zero, net migration is approximately 154.900 units. Inflation has a significant positive effect, being associated with an increase of 0.0674 units in net migration for each one-unit increase in inflation. By contrast, gross debt, the mortality rate, and oil production have significant negative effects, being associated with decreases of 11.380 units, 3.907.000 units, and 348.900 units in net migration, respectively, for each one-unit increase in those variables. These findings are valuable for understanding how these economic variables influence population movements and migration.

Similarly, in model (7), the positive coefficient for the variable “inflation” indicates that a one-unit increase in inflation is associated with a rise of 0.0626 units in net migration. Conversely, the negative coefficient for the variable “gross debt” suggests that a one-unit increase in gross debt is associated with a decrease of 6.612 units in net migration. The constant is not statistically significant ($p = 0.555$), indicating that its value does not exert a statistically relevant effect on net migration when all other independent variables are zero. Together these results are fundamental to understanding the economic mechanisms underlying population movements and migration, highlighting the importance of inflation and gross debt as influential factors in this context.

4.1 FMEA AND ETA RESULTS

This section presents a structured approach based on the Failure Mode and Effects Analysis technique, widely used across various engineering fields, to identify, categorize, and prioritize the possible contributing factors that led to the emergence of this migration crisis. Through this detailed investigation, the objective is to provide a comprehensive and well-grounded analytical framework that can contribute meaningfully to understanding the origins and implications of the Venezuelan migration crisis and, consequently, support the development of effective and sustainable strategies to address it. Table 3 presents a comprehensive analysis of failure modes and their relevance in the context of the Venezuelan migration crisis. The assessment of the Risk Priority Number indicates that, for the Bard system, the main failure modes are associated with a sharp decline in oil production and economic instability, whereas for the ChatGPT system, the principal failure modes relate to mortality and collapse of the health system, along with runaway inflation. Figures 1 and 2 provide a graphical analysis of the RPN and allow an examination of the relative importance of each failure mode.

Table 3

FMEA for the Migration Crisis in Venezuela, BARD vs. ChatGPT

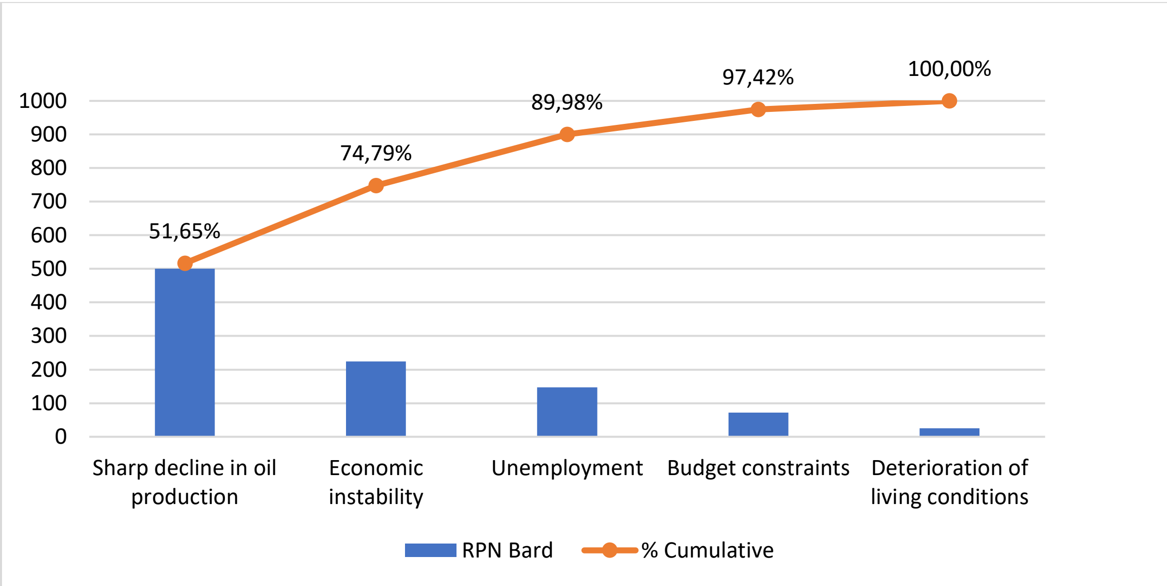
Failure Mode	Severity	Occurrence	Detectability	RPN
BARD				
Sharp decline in oil production	10	10	5	500

Economic instability	8	8	4	224
Unemployment	7	7	3	147
Budget constraints	6	6	2	72
Deterioration of living conditions	5	5	1	25
ChatGPT				
Mortality and collapse of the health system	9	7	9	567
Runaway inflation	9	8	7	504
Rising gross debt	8	7	8	448
High unemployment	8	9	6	432
Drop in oil production	7	6	8	336

Source: Google (2023) and OpenAI (2023).

Figure 1

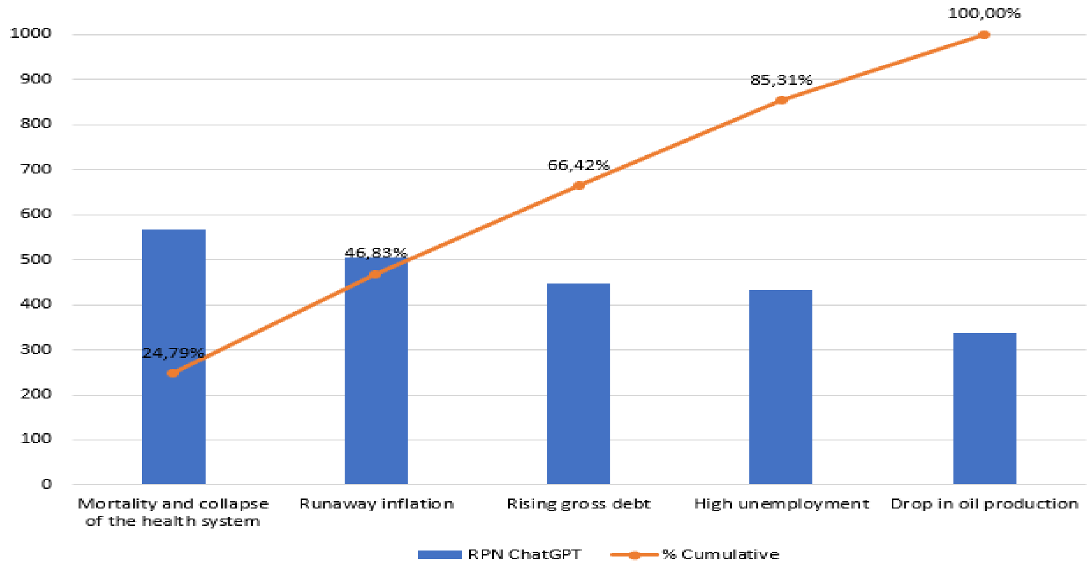
RPN (Risk Priority Number) analysis, Google Bard



According to Figure 1, the analysis conducted with Google Bard identifies that the two main failure modes in Venezuela's migration crisis are the sharp decline in oil production and economic instability, which together account for approximately 74.79% of risk prioritization. This concentration suggests a relationship close to the Pareto optimum or the 80–20 rule, which proposes that, in many situations, approximately 80% of effects are caused by 20% of causes. In this context, it indicates that most of the crisis's impact is driven by a relatively small set of critical factors, underscoring the importance of these priority failure modes in triggering and shaping the evolution of the Venezuelan migration problem.

Figure 2

RPN (Risk Priority Number) analysis, ChatGPT



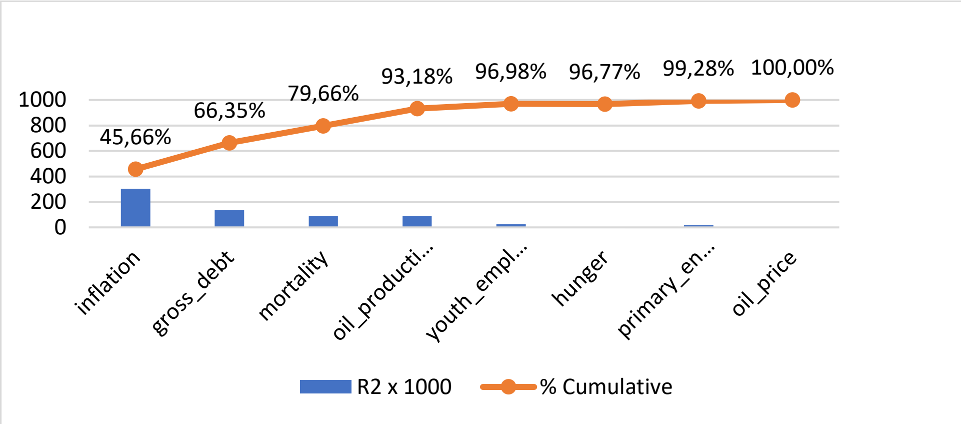
Based on Figure 2, it can be observed that the ChatGPT analysis identified four principal failure modes during the Venezuelan migration crisis: mortality and collapse of the health system, runaway inflation, rising gross debt, and high unemployment. By totaling 85.31% of the risk prioritization associated with the crisis, these factors approach the Pareto optimum indicated by the system.

As a complement, Figure 3 presents a detailed analysis of failure modes using the robust regression models developed in the previous section. Prioritization was based on the R^2 criterion, widely used in regression analysis to measure the model's fit to the observed data. The relative relevance of each variable was calculated through the change in the model's coefficient of determination R^2 after its removal during the iterative process. This approach makes it possible to understand each factor's contribution to the model and facilitates the identification of critical aspects in risk analysis.

Through Figure 3, it is observed that inflation, gross debt, and mortality jointly account for 79.66% of the explanatory power of the robust econometric regression models, approaching the Pareto optimum. This observation indicates that these three factors play an important role in understanding the Venezuelan migration crisis, making them priorities due to their significant association with the phenomenon under analysis.

Figure 3

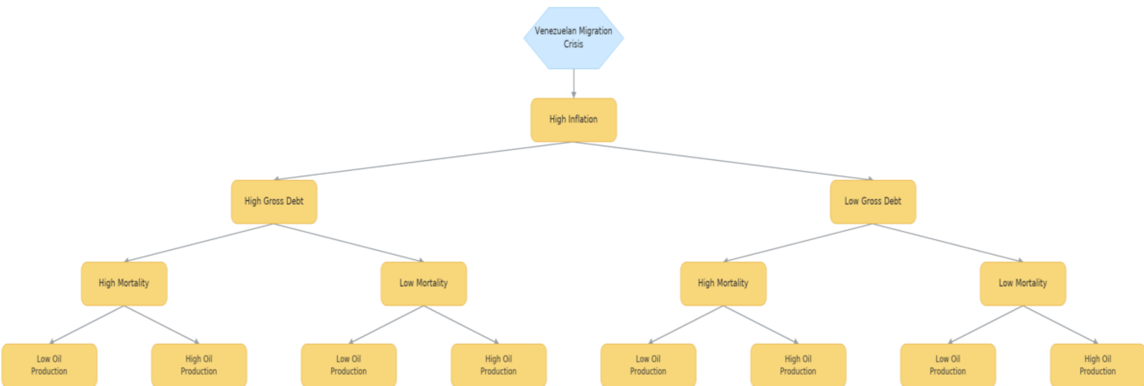
Failure Mode Analysis based on the coefficient of determination R²



Through ETA, it was possible to investigate the multiple branches of the critical events that led to the migration crisis, analyzing the underlying causes and their interconnections. The ETA in Figure 4 indicates that the Venezuelan migration crisis was driven by a series of interconnected events. The final event of interest is mass population migration, and the underlying causes include high inflation rates, rising gross debt, elevated mortality, and declining oil production. These socioeconomic factors created an environment of instability, high unemployment, and widespread socioeconomic hardship, leading many Venezuelans to seek better opportunities in other countries.

Figure 4

Event Tree Analysis in Venezuela Case



5 CONCLUSION

In general, conducting social and economic experiments on topics involving public policy can become subject to ideological debate and personal opinions. This article chose to conduct an analysis based on observable variables to identify patterns, trends, or changes over the period from 1998 to 2022. Building a literature-grounded model to characterize the Venezuelan migration crisis as an undesirable event, using econometric regressions with an AI synchronized to a copilot trained to perform statistical significance analysis in the context of humanitarian causes, can be useful for better understanding the factors that affect these causes and for identifying more effective strategies to address them. The AI can be trained to collect, organize, and analyze large volumes of data related to humanitarian causes—such as demographic information, socioeconomic indicators, and health data—and to identify correlations among variables and the factors most relevant to the success or failure of a specific humanitarian cause.

The academic relevance lies in experimenting with an AI synchronized to a copilot with high computational power that, through data processing, can be trained to perform statistical significance analysis to characterize the Venezuelan migration crisis as an undesirable event, identifying the main variables that generate its failure modes, provided that all necessary datasets and correct commands are supplied.

Finally, the analysis can be valuable for three reasons. First, it avoids polarization by relying on observable variables, ensuring impartiality by focusing on data and evidence rather than ideological opinions. Second, with the use of artificial intelligence and a qualified copilot, it is possible to develop complex and objective models, enabling broader analysis and the identification of important correlations among variables. Third, the proposed analysis does not deviate from the core of the crisis with social and humanitarian issues such as quality of life and conditions for development as relevant factors that drive migration, so this data-driven and objective approach provides a clearer view of the problems at hand, contributing to informed, evidence-based decision-making aimed at mitigating the crisis's negative impact and seeking sustainable solutions and adequate assistance for the most vulnerable populations.

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