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Social Sustainability and Resilience in Supply Chains of Latin America on COVID-19 Times: Classification Using Evolutionary Fuzzy Knowledge

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Abstract: The number of research papers interested in studying the social dimension of supply chain sustainability and resilience is increasing in the literature. However, the social dimension is complex, with several uncertainty variables that cannot be expressed with a traditional Boolean logic of totally true or false. To cope with uncertainty, Fuzzy Logic allows the development of models to obtain crisp values from the concept of fuzzy linguistic variables. Using the Structural Equation Model by Partial Least Squares (SEM-PLS) and Evolutionary Fuzzy Knowledge, this research aims to analyze the predictive power of social sustainability characteristics on supply chain resilience performance in the context of the COVID-19 pandemic with representative cases from Mexico and Chile. We validate our approach using the Chile database for training our model and the Mexico database for testing. The fuzzy knowledge database has a predictive power of more than 80%, using social sustainability features as inputs regarding supply chain resilience in the context of the COVID-19 pandemic disruption. To our knowledge, no works in the literature use fuzzy evolutionary knowledge to study social sustainability in correlation with resilience. Moreover, our proposed approach is the only one that does not require a priori expert knowledge or a systematic mathematical setup.

Keywords: social sustainability; resilience; supply chain; Latin America; fuzzy logic; evolutionary algorithm; SEM-PLS

MSC: 68T05; 62P25

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1. Introduction

The sudden interruption in global supply chains due to the confinement during the COVID-19 pandemic undoubtedly impacted the profitability and permanence of several supplier companies, especially in emerging economies. Correspondingly, it has provided lessons in that decision-makers now know how to manage uncertainty and have learned how to be resilient to future disruptions and identify risks, improve their impacts, and quickly return to normal conditions after the interruption to sustain their functions; in addition, they have considered elementary operations in the performance of internal integration, continuity, agility, and even strategies for sustained competitive advantage [1]. Moreover, a resilient, sustainable supply chain seeks and has the customer himself and his satisfaction as the ultimate verifier [2].

The aspects that contribute to the resilience of the supply chain are multifactorial. However, sustainability has been considered one of them. In [3], the authors paved the way by exploring and demonstrating sustainability as a factor of resilience in the supply chain, considering the environmental and social aspects. Based on a fuzzy multi-objective mathematical model, their analysis integrates resilience and sustainability into a strategic design to seek compensation solutions from a resiliently sustainable supply chain.

Focusing on the community dimension, Hooks, Macken-Walsh, McCarthy, and Power [4] showed how the sustainable social dimension of social cohesion and cooperation among farmers provided supply chain resilience in Ireland's rural farming sector. The same result appears in [5]; by merging the criteria of the LEAN philosophy and the management of the green supply chain, the authors found that increasing efficiency by reducing resources in the supply chain favors resilience in the links of the food sector, thus bringing an impact of social welfare to the community with food supply and with sufficient control and stability in the local supplier companies of the base of the pyramid. Environmental and social sustainability favor the chain's resilience, minimizing the scope of the so-called "domino effect" phenomenon. The above-mentioned describes the cascading effect triggered by the interruption of some link in the chain, gradually affecting the others. The work of Ivanov [6] showed that taking care of social aspects favors the prompt recovery of efficiency, reduction in storage points, inventory security, management of social and environmental risk management, and the strengthening of factories and downstream providers.

Studies have already shown that collaboration with a socially sustainable partner in the production links is not just an aspect of social responsibility with an exogenous impact on company management. Instead, it has been shown that the culture and practices of sustainability in the supply chain are linked to internal strengthening and bring advantages to the operational performance of the supply chain [7,8]. Socially sustainable performance within the supply chain positively affects the company's economic performance, as evidenced by a study in Sri Lanka, South Asia [9]. Due to the convenience mentioned above, it has become an urgent issue for the supply chain to address social problems within the chain (upstream and downstream), especially concerning labor conditions in emerging countries such as health and safety, child and bonded labor, employee education, wages, human rights, gender diversity and discrimination, sanitation, philanthropy, engagement, community employment, as relevant social issues for the manufacturing sector [8].

In the disruptive context of the pandemic, the social aspects of sustainability in the supply chain's resilience have been notorious [10]. In the context of the pandemic, the strategic rooting in strengthening the chains has been vital, from urgent preventive care for the health of society [11] to regional support, where it has brought about a double advantage for resilience. Moreover, it sustained regional development, and in turn, the strengthening of the link with regional suppliers contributed to the recovery of the chain in emerging contexts in Brazil [12].

Nevertheless, during the pandemic, the risk of internal society in companies has become more acute since it has had severe social implications for the livelihoods and well-being of workers and their families. In addition, due to the disruption in supply chains, audits for the care of social issues within companies decreased. The above is a vulnerable context for workers and employers seeking the survival of businesses at the expense of labor rights [13]. Although the suggestion of the pre-pandemic and in-pandemic literature continues to invite the study of social sustainability in the supply chain and demonstrate the role that sustainability has within resilience, said correlation is not necessarily simple, linear, and synchronous. The consideration of resilience is usually with a short-term view, with an immediate reaction to incorporating efficiency. However, sustainable actions do not immediately affect the resilience and performance of the chain [14], so it is necessary to study resilience within the chain from a complex perspective [12]. One way of dealing with these confounding variables within the chain is the path taken by Soleimani et al. [15], who propose a Genetic Algorithm to solve a fuzzy mathematical programming model for optimization purposes in the green supply chain. In a systematic review, we found that several studies have used fuzzy techniques to analyze sustainability and could be categorized into three groups: those from the business perspective within a sector, those specialized in social sustainability, and those that analyzed resilience within the supply chain. Among the studies in the business sector, those in the transport sector stand out, e.g., the research conducted by Bandeira et al. [16], who evaluated sustainability in Brazilian urban transport, or that of Djekic et al. [17], who proposed a sustainable index in the Serbian dairy transport sector. Other business studies have focused on social sustainability in the industrial sector, such as Rajak and Vinodh [18] in India or Cao et al. [19], who proposed techniques to assess the aspects of social sustainability in the manufacturing company. Furthermore, the works of Hendiani and Bagherpour [20] and Rostamnezhad et al. [21] evaluate the social aspects of sustainability in the construction sector. Several works on sustainability within supply chain resilience have shown how fuzzy models effectively handle data uncertainty in real scenarios. Some examples are the multi-objective fuzzy mathematical fuzzy model of Fahimnia and Jabbarzadeh [3] in a case evaluated in a sportswear multinational based in Australia and China; or the mixed integral multi-objective nonlinear programming model used by Baghizadeh et al. [22], in the Iranian tire industry and, recently, Lotfi et al. [23], who used a hybrid fuzzy approach with stochastic programming in the study of the Sustainable Healthcare Supply Chain (Table 1).

To the extent reviewed here, it is shown that the works that have used fuzzy techniques sustain a triple methodological constant:

1. Fuzzy mathematical programming that aims at operational optimization.
2. Fuzzy multi-criteria decision-making methods.
3. Fuzzy inference systems using expert knowledge or systematic mathematical tuning.

Our work seeks to differentiate itself by using fuzzy evolutionary knowledge, not to optimize but to take out-of-sample prediction of a bivariate predictive relationship between social sustainability and chain resilience based on a fuzzy engine based on machine learning.

Table 1. Research on sustainability and its forms of discovering the fuzzy knowledge.

Cite	Technique	Approach	Expert Knowledge	Systematic Configuration	AI	Aspects/Region
[18]	FIS	Decision-making	✓	✓	No	Social sustainability automotive sector in India.
[19]	FIS	Decision-making	✓	No	No	Social sustainability manufacturing sector.
[3]	Fuzzy Goal Programming	Optimization	✓	✓	No	Supply chain sustainability and resilience. China–Australia.
[15]	Fuzzy Multi-objective	Optimization	No	No	✓	Green supply chain.
[16]	Fuzzy Multicriteria	Decision-making	✓	✓	No	Sustainable urban transportation in Brazil
[24]	Fuzzy Multi-Objective	Optimization	✓	✓	No	Sustainable supply chain networks.
[25]	Fuzzy DEMANTEL-ANP	Decision-making	✓	✓	No	Sustainable project management in construction.
[17]	FIS	Decision-making	✓	✓	No	Transportation sustainability index in Serbia industry.
[26]	FIS	Decision-making	✓	No	No	Corporate sustainable European automotive case.
[27]	Fuzzy AHP	Decision-making	No	✓	No	Supply chain economic and social sustainability
[20]	FIS	Decision-making	✓	✓	No	Social sustainability in construction industry.
[21]	Fuzzy DEMATEL	Decision-making	✓	✓	No	Social sustainability in construction projects.
[28]	Fuzzy AHP	Decision-making	✓	✓	No	Social sustainable supply chain automotive sector in Turkey.
[22]	Fuzzy Mathematical Programming	Optimization	✓	✓	No	Resilience and sustainable supply chain Iran
[14]	Fuzzy AHP/Fuzzy TOPSIS	Decision-making	✓	✓	No	Sustainable supply chain logistics Vietnam.
[29]	Fuzzy multi-objective	Optimization	✓	✓	No	Resilience and sustainable supply chain.
[23]	Fuzzy Mathematical Programming	Optimization	No	✓	No	Resilience and sustainable healt care supply chain.
This work	Evolutionary Fuzzy Knowledge	Machine Learning	No	No	✓	Social sustainability and resilience Mexico/Chile.

Evolutionary Algorithms (EAs) are a powerful search technique in the field of artificial intelligence, where a fitness function guides a search through an evolutionary process. The fitness function maximizes or minimizes the desired objective function. Examples of approaches inside the EAs field are Genetic Programming (GP) [30], Evolutionary Strategies (ES) [31], and Genetic Algorithms (GAs) [32]—the GAs being versatile for applications. The hybridization between Evolutionary Algorithms and Fuzzy Logic is known as Fuzzy-Evolutionary Systems [33], Fuzzy-Genetic ones being widespread based on GAs. Therefore, Fuzzy Logic in hybridization with Evolutionary Algorithms to discover knowledge (fuzzy evolutionary approach) is convenient, which allows the elaboration of models to obtain crisp numerical values from the concept of fuzzy linguistic variables. Using a Fuzzy Inference System (FIS) requires expert knowledge to define their fuzzy knowledge base, a knowledge base that will have the biases of the expert who defines their knowledge. In the case of the absence of an expert, a systematic setup to minimize the FIS error can be performed. However, the approaches mentioned above are not guaranteed as optimal. We distinguish two optimal values in the optimization literature: local optima and global optima. Local optima are solutions that seem best in their near search region, while a global optimum is the best of all possibilities. Systematic configurations and expert knowledge lead to a local optima solution, leading to the not optimal performance of the FIS. Genetic Algorithms (GA) can escape local optima to improve even more, which is the principal motivation in this study—to use artificial intelligence (GAs) to automatically configure the knowledge base of the FIS without biases.

Two main areas of Fuzzy-Evolutionary systems appear in the literature: (i) the adaptation of parameters and operators for optimization [34,35], and (ii) the fuzzy control system design, using EAs to discover the knowledge base of a FIS. Our work is related to knowledge discovery, and we will mention some relevant publications next. In [36], the gold price prediction is studied, the algorithm FURIA [37] performs the fuzzy rules generation, and an evolutionary algorithm tunes their trapezoidal membership function parameters. The width of the membership functions of a controller for a robot trajectory is optimized in [38]. Reference [39] fine-tuned a Fuzzy Controlled Charging System for Lithium-Ion Batteries by a GA. The non-invasive measurement of a stroke volume was conducted through the discovery of fuzzy rules by a GA [40]. Some other examples are crop plantation identification [41], breaking systems [42], and prediction of pipe failures in water supply networks [43]. Furthermore, a considerable diversity of applications using Fuzzy-Evolutionary systems can be found in the works [44–54], among others in the literature. In this work, we use a Genetic Algorithm to produce the set of fuzzy rules.

Several social sustainability works have dealt with real-life scenarios and show how fuzzy models deal effectively with data uncertainty. Some examples are the multi-objective fuzzy mathematical model of Fahimnia and Jabbarzadeh [3], the multi-objective mixed-integer nonlinear programming model used by Baghizadeh, Pahl, and Hu [22], and recently Lotfi, Kargar, Rajabzadeh, Hesabi, Özceylan [23], who used a hybrid fuzzy with a stochastic programming approach, among others. In this work, as a methodology, the following steps are followed: (i) a survey of supply chain managers in Mexico and Chile for data collection, (ii) the collected data are unified and validated in second-order constructs through a Structural Equation Model by the Partial Least Squares method (SEM-PLS) with the SmartPLS software, (iii) two databases are constructed, one for Mexico and one for Chile, and integers represent the nominal values; (iv) a GA refines the fuzzy outputs of the FIS, substituting the need for expert knowledge using the Mexico database as training data; (v) finally, using Chile's database as testing data, we compute the FIS error. Figure 1 summarizes the methodology of the work.

Therefore, the objective of this paper is, through the application of a fuzzy evolutionary approach, to evaluate under uncertainty the predictive conditions of social sustainability factors in the resilience of the Latin supply chain in the context of the COVID-19 pandemic, with a representative case of Mexico and Chile. The study's method, results, conclusions, and social and managerial drivers are presented.

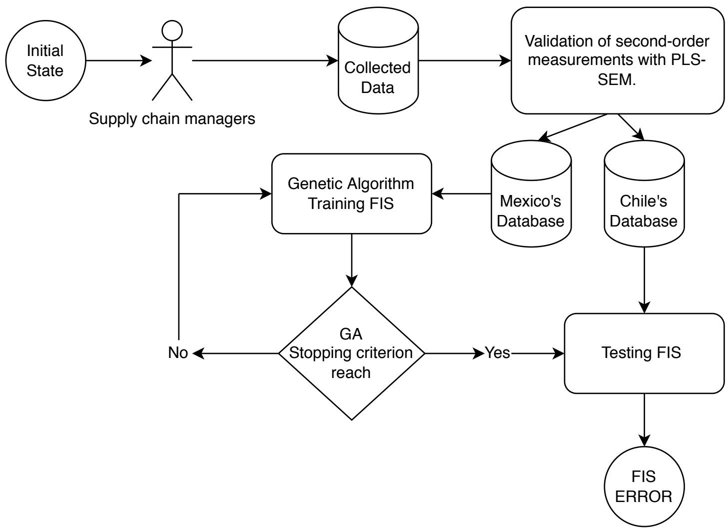

Figure 1. The diagram of the methodology employed in this work.

2. Methodology

This research employs empirical statistics, and the purpose of this research, according to Wacker [55], is to empirically verify the theoretical relationships in larger samples of real businesses. The research has two major phases:

- Validation of the measurement model in terms of its validity and individual consistency and constructs and, finally, simplifying the model with latent measures and second-order constructs.
- The application of the fuzzy evolutionary approach

2.1. Measurement Constructs

The instrument's build employs measures already validated by Mani et al. [8], who proposed dimensions in a model to measure social sustainability in the supply chain. Four constructs with four items were used from the said model, resulting in a list of sixteen measures. The first construct is labor rights (adequate working conditions, strict policy for the prohibition of forced child labor, periodic labor audits by clients and strict monitoring of violations of labor rights); the second construct is health and safety (strict health and safety policy in the workplace, health and hygiene assurance, assurance of drinking water and sanitation in the community, guide for the implementation of occupational health and safety measures); the third construct related to social responsibility (development of local suppliers—provider of the supplier, philanthropic activities/disinterested help and carry out programs to generate opportunities to develop skills for unemployed youth); and the fourth construct is inclusion (employment of locals, women, people with disabilities, marginalized and minorities, policies of gender equality and non-discrimination, growth opportunity for each employee equally based on merit, and rights and privileges to the employee regardless of age, sex, race, community, religion or nationality).

For the resilience construct of the supply chain, we use the model proposed by Mandal and Dubey [56], which consists of six items (ability to return to its original state after being interrupted quickly, ability to maintain the desired level of connection between its members at the time of disruption, ability to maintain the desired level of control over structure and function at the time of disruption, knowledge required to recover from disruptions and unexpected events, financial capacity to cope with the consequences to shocks and infrastructure capable of responding quickly to shocks). Both measures are in the context of the emerging economy of India. In addition to the general information questions, we formed an instrument of 22 items in 5 constructs. The corresponding corrections to the wording and clarity of the terms were piloted to determine validity and readability, as

Heeler and Ray [57] proposed. Later, the survey was sent to a group of experts: academics for methodological contributions and supply chain professionals. Experts proposed minor changes and modifications to the questionnaire items. We made the corresponding changes and modifications.

2.2. Sampling and Collection of Information

Purposeful sampling is employed to extract the relevant information from the group of people [58]. The information was collected through the database of the professional network Linkedin, guaranteeing that the subjects who met the profile of purchasing management or supply chain management answered the survey directly from their account. The search criteria in the professional network were using the keywords "purchasing manager" and "supply chain manager," generating the search in English and Spanish and filtering by country, Mexico and Chile, thus inviting them to connect to the network, and those who accepted received a personal message inviting them to answer the survey. Between August and December 2021, we received nearly 1000 questionnaires, of which 151 useful ones were received, with a general response rate of 15.1%. Binational responses from Mexico (n = 80) and Chile (n = 71) were selected (Table 2. The constructs were validated using the SmartPLS 3 structural equation program [59].

Table 2. Sample characteristics.

Characteristic	Classification	Frequency	%
Country	Chile	71	47.02
	Mexico	80	52.98
	Total	151	100
Size	Large	97	64.24
	Medium	19	12.58
	Small	21	13.91
	Micro	14	9.27
	Total	151	100
Commercial coverage	Global	50	33.11
	Latin America	21	13.91
	Local/regional	20	13.25
	National	60	39.74
	Total	151	100
Experience in years in supply chain	0–5	45	29.80
	6–10	18	11.92
	11–20	36	23.84
	$\geq$20	33	21.85
	Total	151	100
Sex	Male	54	35.76
	Female	97	64.24
	Total	151	100

2.3. Database and Feature Selection for Machine Learning

Firstly, we want to present the Pearson correlation coefficient of every criterion associated with supply chain resilience (Figure 2).

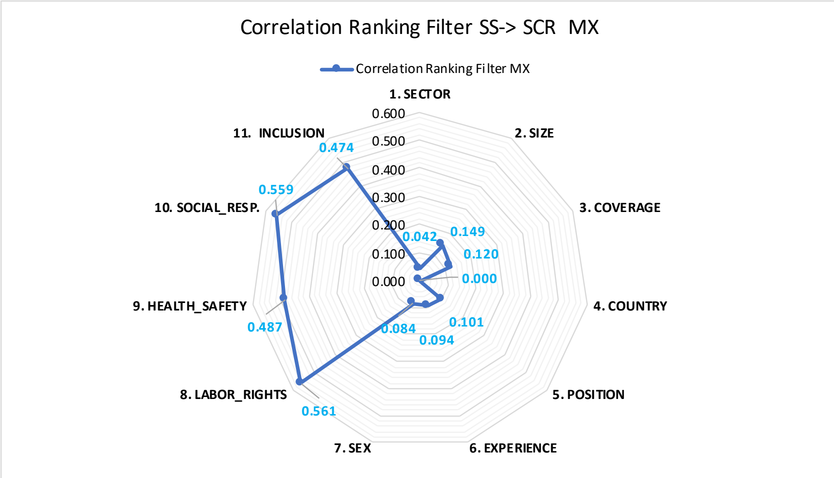

Figure 2. Ranking of the Pearson correlation coefficient for Mexico's data.

According to Mexico's data of the ten criteria subjected, issues such as sector, company size, experience, or gender of the managers interviewed showed an irrelevant correlation with supply chain resilience. However, the social aspects of social sustainability showed a significant correlation with the resilience of the Latin supply chain analyzed. The above aligns with Fahimnia and Jabbarzadeh's [3] work, supporting the correlation between sustainability and chain resilience. The most crucial aspect was labor rights, which can be identified as a sustainability criterion linked to the internal society of the links (see Rajak and Vinodh [18]), which are the employees, as are internal inclusion and non-discrimination and health and safety, which also showed a correlation. On the other hand, the criterion of social responsibility correlates significantly with the chain's resilience. This aspect can be related to the commitment of the supplier companies to the external society, which is the community (see Rajak and Vinodh [18]). These results are consistent with the findings in the Irish supply chain shown in the work of Hooks, Macken-Walsh, McCarthy, and Power [4]. They evidenced the association of community governance of farmers as a socially sustainable aspect that impacted a resilient chain capable of reacting quickly to disruption—according to Chile's data, taking into account the same non-relevant criteria (Figure 3).

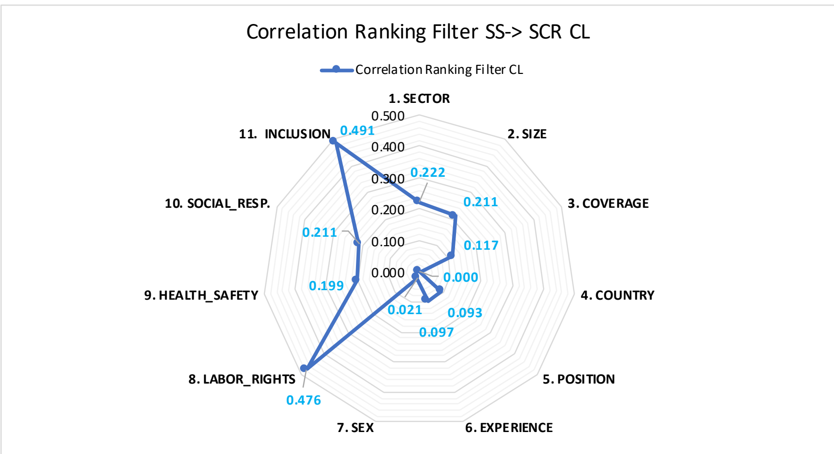

Figure 3. Ranking of the Pearson correlation coefficient for Chile's data.

Chile's data showed that the most relevant criteria were labor rights and inclusion, and the least correlated were health and safety. Socio-demographic aspects were also irrelevant. The joined data of both real representative cases of the supply chain in Mexico and Chile are shown in Figure 4, the country criterion was not relevant.

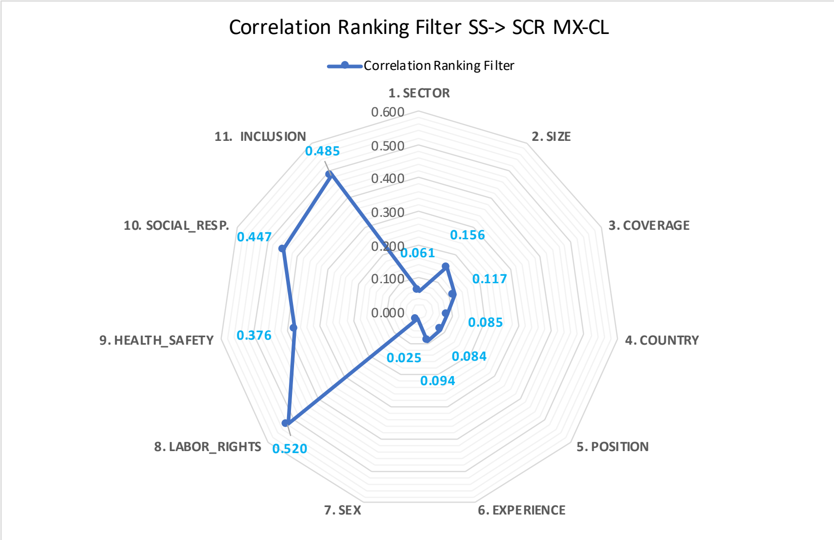

Figure 4. Ranking of the Pearson correlation coefficient for Mexico's and Chile's data.

Our final database was made up of more than 150 enterprises of different sizes and sectors, survey results from people at different organizational ranks with eleven characteristics, the four constructs mentioned above, the items from Table 2, and a construct to measure the resilience of the supply chain. We collected actual data from two representative countries of Latin America, Chile and Mexico, for our research and built their respective constructs (labor rights, health and safety, health and hygiene assurance, social responsibility, and inclusion). We selected relevant features for the above characteristics by computing the Pearson correlation between the attributes and the class (resilience of the supply chain) and ranking them. We found that four characteristics were ranked higher: labor rights, inclusion, social responsibility, and health/social safety, in that respective order. Therefore, we select those four features as inputs in our machine learning model. The database can be consulted at https://github.com/AASantiago/MEX-CHL-Resilience-DB (accessed on 1 January 2022).

2.4. Fuzzy Logic Basics

Fuzzy Logic introduced by Zadeh [60] extended the classical Boolean logic. In Boolean logic, the statements have two possible answers—true or false, while in Fuzzy Logic, the statements have a degree of truthfulness known as a degree of membership. A mathematical function maps input values to a membership degree as a real number $\in [0,1]$ (1.0 for 100% membership degree). The triangular membership function (see Equation (1)) is a regular selection in many studies, and in this work, due to its simplicity and effectiveness, plotting the function shapes a triangle beginning in the parameter a, with the peak in b, ending in c.

$$\mu_A(x) = \begin{cases} 0 & if \quad x \leq a \\ \frac{x-a}{b-a} & if \quad a \leq x \leq b \\ \frac{c-x}{c-b} & if \quad b \leq x \leq c \\ 0 & if \quad c \leq x \end{cases} \tag{1}$$

The triangle represents a fuzzy set, mapping inputs to different membership degrees. In this work, we use three granularity levels for the inputs and outputs: low ($a = -0.4$, $b = 0.0, c = 0.4$), mid ($a = 0.1, b = 0.5, c = 0.9$) and high ($a = 0.6, b = 1.0, c = 1.4$). We can determine a Mamdani Fuzzy Inference System (FIS) using linguistic rules and fuzzy sets. The rules of a FIS (also known as a knowledge base) are of the type IF-THEN, and for practical purposes, we implement AND rules. In an FIS, the usual operation for AND rules is the minimum as follows:

$$\mu_{A \cap B} = \min(\mu_A, \mu_b) \tag{2}$$

Equation (2) computes the "and" operation by taking the minimum of the two or more membership values; once computed, the degree slices the fuzzy output of the rule as a result of the rule application. The results of all fuzzy rules are combined to obtain one fuzzy output. For real applications, it is desired to come up with a single crisp output from an FIS using a process called defuzzification. A widely accepted defuzzification is the center of mass calculation, implemented in this work as follows:

$$z = \frac{\int \mu_A(x)xdx}{\int \mu_A(x)dx} \tag{3}$$

where z is the center of mass, and μ_A is the membership function A evaluated at x. We use the crisp outputs z for training our fuzzy knowledge base.

2.5. The Fuzzy Inference System

In this work, we implement a Mamdani Fuzzy Inference System [61] to predict resilience with our available database from Section 2.3. Mamdani Fuzzy Inference Systems use linguistic variables such as hot, warm, or cold instead of numeric thresholds to preserve the uncertainty of the attributes. Using the linguistic variables, a set of rules known as the knowledge database maps the inputs of the FIS to the desired output, also as a linguistic variable. In our particular case of AND rules, we use the min operator in Equation (2) to slice the fuzzy output of the rule to later be defuzzified using the centroid method from Equation (3), producing a crisp value. In other words, given the corresponding inputs for a supply chain resilience value (a surveyed example), we want the FIS to produce the same crisp output as the example. The idea is to discover a knowledge base that minimizes the error between the crisp output of the FIS and the training example's numeric values. After analyzing relevant features from Section 2.3, we decided to take four inputs for an FIS implementation: labor rights, health/social safety, social responsibility, and inclusion, and as a dependent value (output), the resilience of the supply chain. The values of the inputs and outputs are normalized $\in [0, 1]$ to be consistent with the fuzzy sets described in Section 2.4. We need to generate the set of AND rules with three granularity levels (low, mid, high) and four inputs, so we have to compute the combinations. The number of combinations with repetition equals k^n, where k is the number of inputs, and n is the number of granularity levels. The above calculation gives 64 AND rules to be tuned by a Genetic Algorithm.

2.6. Evolving Knowledge through a Genetic Algorithm

Although the number of fuzzy rules in our knowledge base is only 64, fine-tuning their outputs is a high computational effort. To enumerate the possible configurations, we need to compute their combinations with repetitions k^n, where k is equal to 3 (the granularity levels), and n is equal to 64 (the number of rules), giving a total of $3.43368382 \times 10^{30}$. Because the above is infeasible to compute in a typical scenario, we use a Genetic Algorithm to tune the FIS knowledge base. For practicality, we only configure the fuzzy outputs of the rules and not the membership function parameters, as already defined in Section 2.4 and used as standard parameters in many studies. We follow the general structure of GAs, as shown in Figure 5.

while ! Stop condition **do**
  $Parent \leftarrow Selection(Pop)$
  $offSpring \leftarrow Crossover(Parent)$
  $Mutation(offSpring)$
  $Pop \leftarrow Pop \cup offSpring$
  $EnviromentalSelection(Pop)$
end while

Figure 5. The Genetic Algorithms framework includes the steps of selection, crossover, mutation, and environmental selection.

The fitness function of the GA directly evaluates the FIS classification error produced by the GA's individuals between the produced crisp output and the actual value in the training database. To tune the 64 rules, the GA uses a string of integers of size 64 as individual (chromosomes) representation, as shown in Figure 6. The integers one, two, and three represent the low, mid, and high granularity levels, respectively, and each integer is the fuzzy output of a rule. As a crossover operator, we implement a single-point crossover, and as a mutation operator, every integer has a probability of being mutated to a random granularity level.

2 2 3 2 1 1 1 2 3 1 3 2 2 2 1 1 3 1 1 1 . . . . 2 1 2 2 1 2 1 1 2 3

Figure 6. Implemented chromosome representation of length 64, which allows an integer for every rule. Number one, two, and three represent the low, mid, and high fuzzy output sets, respectively.

3. Experimental Setup

This section describes the experimental settings and how the data are validated. The split validation approach validates the FIS performance as other machine learning studies. Chile's data are the training data for the FIS in the GA, making up 70 examples. The parameters for the GA execution appear in Table 3. Due to the stochastic nature of the GAs, we perform 30 independent executions of the GA; the best solution from the 30 executions is the representative solution. With the best-found solution, we compute the relative percentage error of the FIS over Mexico's 81 examples (the testing data).

Table 3. Parameter settings for the proposed Genetic Algorithm.

	GA
Crossover:	Single-point
Crossover probability:	$p_c = 1.0$
Mutation:	Random value
Mutation probability:	$p_m = 1.0/n$
Population size:	100
Generations:	250

4. Results

Using the statistical software SmartPLS 3.3.7 [59], we performed a reliability analysis to assess the internal consistency of the latent variables. To better the consistency of the measures, we generated second-order coefficients for social sustainability and resilience measures in the supply chain. They result in a single construct of social sustainability. The measurement model of both the first and second models was validated.

At first, the individual reliability of the indicators was verified, where the expected threshold is an external load $\lambda \geq 0.708$; although, in social sciences, indicators with a load $\lambda \geq 0.500$ are valid for reliability [62]. In the first analysis of two indicators, the external loads obtained a value between 0.996 and 0.597. Then, we assessed the composite reliability of the construct, where there should be values > 0.70 [62]. The values to evaluate the consistency of the composite reliability constructs ranged between 0.827 and 0.940 and, in terms of the Average Variance Extracted (AVE), the parameters were acceptable, $\geq$0.5. We check the discriminant validity of the constructs, ensuring that the constructs were empirically different from the other constructs included in the structural model. We use the heterotrait-monotrait (HTMT) correlation ratio, that is, the average of the correlations of the indicators between constructs, as well as within the same construct [63]. The threshold value for the HTMT criterion was far from one with a limit of $\leq$0.800, thus concluding that there is discriminant validity [62]. Finally, we evaluate the variance inflation factor (VIF), used to evaluate the collinearity of the indicators, where they had satisfactory values ≤ 3, according to [62]. The model's predictive power within the sample had an R^2 of 0.318, while the values of f^2 in the first-order model were irrelevant $<$0.02.

For the sake of parsimony in the explanation of the model and preparation for a mathematical explanation of the fuzzy knowledge logic technique, we decided to generate a construct of second molecular order from the measures related to social sustainability, prioritizing information on the common variance effect, that is, the variance shared by each of the dimensions [64]. The coefficients of the latent variables were taken from the result of the validation of the first-order measurement model. The resulting values were validated. Table 4 shows the values of satisfactory latent loads (λ) for the case of the new construct of the second-order of social sustainability (SS), with satisfactory values that oscillate between 0.789 and 0.873. The latent variable of resilience in the supply chain (RES_SC), with a load value (λ) of 1, is due to the one-dimensional condition of the latent variable coefficient. The construct items, coefficients, and latent variables have satisfactory composite reliability and AVE values. It is clear how the model within the sample substantially improves the effect size of f^2 with a value of 0.438, going from an almost null effect to a medium one. The HTMT criterion also improved, being further from one, with a value of 0.591.

Table 4. Individual reliability of the item and convergent validity of the construct: second order.

Construct	**Loads (λ)**	**Cronbach (α)**	**Composite Reliability**	**AVE**
I. Social Sustainability (f^2, 0.438)		0.856	0.903	0.699
1. Labor rights in SC	0.873			
2. Healt and safety in SC	0.789			
3. Social responsability in SC	0.812			
4. Inclusion in SC	0.867			
II. Resilience in SC (R^2, 0.305) (HTMT, 0.591)		1.000	1.000	1.000

It is essential to notice that Genetic Algorithms are stochastic by nature, but we are not determining the performance of the GA; instead, we are benchmarking the performance of the FIS. FISs are deterministic; therefore, we can compute the exact relative error value produced by the best-found fuzzy knowledge database in the training phase against the test data (Mexico's data). The best fuzzy rules found by the GA in the training phase are in Table 5. With the rules from Table 5, we compute an absolute error of 12.97, equivalent to about 13 examples wrongly classified from 81, with an 84% classification accuracy; however, this absolute error could be the sum of slight differences between crisp values, and for some decisions makers, these differences would be insignificant. Therefore, we have a predictive power of the resilience in the supply chains of more than 80%, based on features related to social sustainability. Our proposed FIS is a powerful tool for decisions and policymakers in organizations.

Table 5. The 64 rules of the Fuzzy Knowledge base.

AND Antecedents				Consequent
Labor-Rights	**Social-Responsibility**	**Inclusion**	**Social-Security**	**Resilience-Supply-Chain**
Low	Low	Low	Low	Low
Low	Low	Low	Mid	High
Low	Low	Low	High	Low
Low	Low	Mid	Low	High
Low	Low	Mid	Mid	Low
Low	Low	Mid	High	Mid
Low	Low	High	Low	Mid
Low	Low	High	Mid	Low
Low	Low	High	High	High
Low	Mid	Low	Low	High
Low	Mid	Low	Mid	Mid
Low	Mid	Low	High	Low
Low	Mid	Mid	Low	Mid
Low	Mid	Mid	Mid	Low
Low	Mid	Mid	High	Low
Low	Mid	High	Low	Mid
Low	Mid	High	Mid	High
Low	Mid	High	High	Mid
Low	High	Low	Low	Mid
Low	High	Low	Mid	High
Low	High	Low	High	High
Low	High	Mid	Low	High
Low	High	Mid	Mid	Low
Low	High	Mid	High	Mid
Low	High	High	Low	Mid
Low	High	High	Mid	High
Low	High	High	High	Mid
Mid	Low	Low	Low	Low
Mid	Low	Low	Mid	Low
Mid	Low	Low	High	High
Mid	Low	Mid	Low	Low
Mid	Low	Mid	Mid	Mid
Mid	Low	Mid	High	Mid
Mid	Low	High	Low	Low
Mid	Low	High	Mid	High
Mid	Low	High	High	High
Mid	Mid	Low	Low	Low
Mid	Mid	Low	Mid	High
Mid	Mid	Low	High	High
Mid	Mid	Mid	Low	High
Mid	Mid	Mid	Mid	High
Mid	Mid	Mid	High	High
Mid	Mid	High	Low	Mid
Mid	Mid	High	Mid	High
Mid	Mid	High	High	High
Mid	High	Low	Low	Low
Mid	High	Low	Mid	High
Mid	High	Low	High	High
Mid	High	Mid	Low	High
Mid	High	Mid	Mid	High
Mid	High	Mid	High	Mid
Mid	High	High	Low	Mid
Mid	High	High	Mid	Mid
Mid	High	High	High	High
High	Low	Low	Low	High
High	Low	Low	Mid	Mid
High	Low	Low	High	Mid
High	Low	Mid	Low	Mid

Table 5. *Cont.*

AND Antecedents				Consequent
Labor-Rights	**Social-Responsibility**	**Inclusion**	**Social-Security**	**Resilience-Supply-Chain**
High	Low	Mid	Mid	High
High	Low	Mid	High	High
High	Low	High	Low	Low
High	Low	High	Mid	Low
High	Low	High	High	High
High	Mid	Low	Low	Low
High	Mid	Low	Mid	High
High	Mid	Low	High	High
High	Mid	Mid	Low	Mid
High	Mid	Mid	Mid	High
High	Mid	Mid	High	High
High	Mid	High	Low	Mid
High	Mid	High	Mid	High
High	Mid	High	High	High
High	High	Low	Low	Low
High	High	Low	Mid	Low
High	High	Low	High	High
High	High	Mid	Low	Low
High	High	Mid	Mid	Mid
High	High	Mid	High	High
High	High	High	Low	Low
High	High	High	Mid	Mid
High	High	High	High	High

From the experimental results, we can assert that we have a second-order model with valid latent variable coefficients for each construct. The above allows parsimony in the data that are appropriate for generating the predictive rules of the fuzzy analysis. Nevertheless, the evaluated supplier cases are low for fair wages, production ethics, and employee training.

5. Discussion and Conclusions

Our fuzzy technique results showed the relevance of social aspects within the business sectors and were consistent with fuzzy evaluation works performed in the business sectors, as is the case of Rajak and Vinodh [18] and Hendiani and Bagherpour [20]. They found social aspects relevant to the company both inside and outside the company. Regarding the relevant aspects in the care of the internal society or human capital, issues such as health and safety practices resulted. Likewise, equal opportunities and education in the workplace also arose. In the aspects referring to the care of the external society or community, issues of support for safety, employment and health systems resulted. Support for smaller suppliers was also relevant.

In the studies focused on the supply chain, our results also show consistency with other findings, such as those of the work of Yıldızbaşı et al. [28] in the automotive sector in Turkey, where the criteria of safety and occupational health practices, non-discrimination and social responsibility with the community and human rights were significant. Likewise, the research of Đurić et al. [27], who employed a fuzzy AHP technique and from the risk perspective, showed the relevance of social aspects in the chain in terms of the risk to the resilience of unhealthy working environments and danger to the health and safety of employees, as well as issues such as human rights, inclusion, benefit to the communities surrounding the links in the chain and the focal companies. Specifically, in the context of the health crisis caused by the COVID-19 disease, there have been recent diffuse studies that evaluate the resilience of the supply chain, some focused on the environmental dimension of sustainability, highlighting aspects such as the optimization of natural resources in the chain (such as the work of Lotfi, Kargar et al. [23]).

Recently, research on chain resilience has reinforced the social aspects of sustainability, such as that of Wang et al. [65]. From a fuzzy logic based on experts, they determined that health and safety are relevant attributes of a socially sustainable supplier within the Vietnamese logistics sector. Likewise, the research of Nayeri et al. [29] assesses, as a socially sustainable factor for chain resilience, the opportunity for permanent jobs and human rights security in the work area. Our results focused exclusively on the relevance of social issues of sustainability. We utilize a fuzzy technique that has scarcely been used in sustainable approaches and supply chain resilience. We propose a Genetic Algorithm for generating fuzzy evolutionary knowledge to predict the bivariate relationship between social sustainability and Latin supply chain resilience through artificial machine intelligence. Although the work of Soleimani et al. [15] also proposes a Genetic Algorithm, they use it for fuzzy mathematical programming, and the distinction between their work and ours is that their model aims at optimization and focuses on the environmental aspect of sustainability and, our model, has an approach focused on prediction and the social aspect of sustainability. Within the sample that our systematic review of the literature yielded, we did not find a work that contains the criteria of our research. This research aimed to analyze the predictive power of social sustainability criteria on the performance of supply chain resilience in the context of the COVID-19 pandemic. In summary, based on fuzzy evolutionary learning, we conclude that the aspects of labor rights, health and safety, inclusion, and social responsibility in the Latin supply chain contribute significantly to the predictability of the supply chain resilience in the representative cases of Mexico and Chile. In terms of managerial implications, a call is made to decision-makers to resize social welfare issues within the links of the chain. These results demonstrate that caring for the welfare of people, inside and outside the supplier companies, is not an issue exogenous to the company. It is not mere external altruism but rather endogenous strategic aspects that impact the capacity to sustain the Latin supply chain in the face of current and future disruptions. We invite supply chain managers to strengthen the supply chain's resilience by taking care of the indicators related to adequate working conditions, strict surveillance of labor rights violations, occupational health, and safety policies for the external society, such as the development of local suppliers, as well as philanthropic activities/selfless help and carrying out programs to generate skill development opportunities for unemployed youth. For future lines of research, we will continue confirming the predictive power of fuzzy evolutionary knowledge concerning the influence of social aspects of sustainability in the Latin supply chain in different contexts, even at different times to know if the results are consistent outside of the pandemic context.

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Abbreviations

The following abbreviations are used in this manuscript:

AVE	Average Variance Extracted
EA	Evolutionary Algorithm
FIS	Fuzzy Inference System
GA	Genetic Algorithm
HTMT	Heterotrait-Monotrait

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