Exploring the mutual influence among the social innovation factors amid the COVID-19 pandemic

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ABSTRACT

From the triple bottom line, the social aspect has received relatively limited attention during the Corona Virus Disease (COVID-19) pandemic, particularly in emerging economies. Social innovation factors help improve the sustainability performance of the companies. This study develops a social innovation decision framework and analyses the interrelationships among social innovation factors considering the COVID-19 situation. For this purpose, the Decision-Making Trial and Evaluation Laboratory (DEMATEL) is extended by integrating the Z numbers and rough fuzzy set theory into its computational procedure. Z-numbers address the uncertainty of the decision and experts' confidence in the evaluation and rough numbers are used for aggregating the experts' opinions. On this basis, the mutual influence of social innovation factors and the influence weights of these factors are investigated. The results suggest that a quick response to market demand for sustainable products is the most influential factor in attaining social sustainability innovation during the pandemic. This article concluded by providing insights for industrial experts and decision-makers to understand the underpinnings of social sustainability innovation during unforeseen situations.

Keywords: Social innovation; sustainability; supply chain management; COVID-19 pandemic; rough numbers; decision analysis.

1. Introduction

Industrialization has negatively impacted society and nature. Adverse social issues, like poverty, corruption, and human rights along the supply chains are the major obstacles to pursuing sustainable development targets (**Silvestre and Ţîrcă, 2019**). Governments are introducing stricter measures to enforce sustainability standards in different sectors; following these directives is necessary to materialize the sustainable development goals (**Kusi-Sarpong et al., 2019**). Corporations should cooperate to alleviate the negative impact of their activities taking into consideration social, economic, and environmental considerations (**Sarkar et al., 2020; Bui et al., 2020)**. As one of the major tenets of sustainable development (**Gupta and Barua, 2018**), sustainable innovation is of high relevance in adjusting operations to alleviate negative environmental impacts and improve socio-economic and organizational performance; it consists of technological, process, and social innovations for energy saving, waste management, and pollution reduction along supply chains (**Howaldt and Kopp, 2012**).

The Corona Virus Disease (COVID-19) outbreak has impacted business operations and interrupted supply chains **(Sarkis et al., 2020)**. The number of COVID-19 patients is increasing rapidly with the delta and lambda variants taking the death toll and infection rate to over 4.3 and 204.9 million, respectively, as of August 2021. Governments have responded by limiting non-necessary business activities, social distancing, minimizing public gatherings, and canceling indoor events with more than a certain number of participants, among other measures **(Sarkis et al., 2020)**. Lack of raw-material and parts (i.e., chip shortage) and delayed deliveries to the final consumers have been the major consequences of lockdown measures. In this situation, the socio-economic and socio-environmental aspects of businesses have been impacted the most **(Gostin and Wiley, 2020)**. The pandemic has made decision-makers adjust their supply chain to a more sustainable standard. In particular, the outbreak of COVID-19 has dramatically increased the importance of human health within organizations **(Hakovirta and Denuwara, 2020)**. Well-informed decisions and initiatives for workplace safety, social distancing, remote working, and health monitoring are much needed to enhance the social aspect of supply chain sustainability in times of pandemic **(Kumar et al., 2020)**. For implementing sustainable supply chains, firms must be innovative and responsive to damaging socio-environmental effects. Sustainable innovation includes completely new or developed products, processes, and techniques that lead to a reduction in harmful socio-environmental effects and improved life quality (**Ahmadi et al., 2020; Kemp, 2000)** The role of the social dimension of sustainable innovation has received very limited attention in the academic literature; a gap that motivated us to explore the mutual influence among social innovation factors considering the COVID-19 pandemic.

To understand the underpinning of sustainable innovation during disaster situations, there is a need to investigate the influence of COVID-19-related circumstances on social factors. Proposing a decision support framework for evaluating the mutual influence among social sustainability innovation factors during the COVID-19 pandemic situation within an emerging economy context using the Rough-Z-DEMATEL technique highlights the novelty of this article. To the best of the authors' knowledge, the mutual influence between the social sustainability innovation factors considering the COVID-19 epidemic situation has not been studied. The outcomes of such analysis show the beneficial and/or detrimental relationships among the factors, which is necessary for suggesting the best course of managerial actions and improving the performance the sustainability practices. The following research questions are sought to address this research gap:

Q1. Which factors are pertinent for investigating the social dimension of sustainability innovation considering the COVID-19 pandemic?

Q2. How do the interdependencies among social innovation factors impact the decisions?

A twofold contribution is defined to answer these questions. First, a set of decision factors are identified through a literature review and interviews with experts to shed light on the social dimension of sustainability innovation decisions during the COVID-19 pandemic. The Decision-Making Trial and Evaluation Laboratory (DEMATEL) can be used to study the interrelationships between the factors pertinent to a decision. The basic DEMATEL is limited in that it cannot address the issue of information uncertainty and ambiguity. Besides, experts' judgments in group decision-making of DEMATEL methods are often integrated using simplistic methods, like simple and weighted averages, which reduces the confidence in the evaluation. Incorporating the Z fuzzy set and rough fuzzy set theories will help overcome these issues in the DEMATEL. As the second contribution, the Rough-Z-DEMATEL technique is proposed to effectively investigate the interdependencies among the social innovation factors during the COVID-19 pandemic situation. Z-numbers reflect the uncertainty and confidence of experts in the evaluation (**Tian et al., 2020**, **Chutia, 2021**) and the opinions of multiple experts can be aggregated using rough numbers (**Yazdani et al., 2020**).

Considering the depth of the COVID-19 catastrophe in the manufacturing sector of emerging economies, case studies from this scope are used to inform other situations. A visual graph, called Influential Network Relation Map (INRM), is constructed to help improve the decision-making process in similar situations. Overall, the outcomes will help managers to understand the influential relationship among the social innovation factors in the evaluation system and make well-informed decisions and strategies for promoting sustainable innovation in the manufacturing sector. Besides, managerial insights and practical implications are provided for industry practitioners and decision-makers.

The remainder of this manuscript is structured as follows. Section 2 provides a review of the most relevant literature. Section 3 elaborates on the research methodology. Section 4 evaluates the applicability of the proposed model and decision framework using a case illustration. Section 5 presents a discussion of the result. Section 6 presents the practical and theoretical implications of the study. Finally, Section 7 provides the concluding remarks and suggestions for future development in the field.

2. Background

2.1. Sustainable supply chain management

Improving the socio-environmental and socio-economic aspects of supply chains is essential for sustainable development (**Ahmadi et al., 2017**). Social pressures, strict regulations, and the growing public knowledge urge companies to utilize sustainability initiatives in their supply chain operations. In this situation, companies are required to establish a balance between their interests and responsibilities pertinent to social, economic, and environmental issues (**Sarkis and Zhu, 2018**). As one of the major drivers of sustainable development, Sustainable Supply Chain Management (SSCM) refers to the initiatives that maximize social well-being and alleviate negative environmental impacts of the relevant operations (**Bui et al., 2020**); it consists of managing the materials, information, resources, and collaboration between the players within the supply chain taking into consideration social, economic, and environmental considerations (**Ahi and Searcy, 2013**). In addition to alleviating the negative impact of supply chain activities, SSCM improves corporates' image and organizational performance (**Vargas et al., 2018**), and helps establish a competitive advantage (**Yu et al., 2019**). A growing number of research papers are addressing SSCM from which, the published works on sustainable innovation are reviewed in the following sub-section.

2.2. Sustainable innovation

Innovation is a prerequisite to achieving sustainable development with maintaining long-term growth being its major pillar (**Silva et al., 2019)**. Innovative approaches are much needed for firms to minimize the negative impacts of their activities and pursue sustainability goals (**Silvestre and Ţîrcă, 2019**). Sustainability innovation can be described as adjusting products and processes to reduce their negative socio-environmental impact **(Beise and Rennings, 2005)**; it benefits companies by improving their social image and profitability **(Aguado et al., 2013)**. Poverty, corruption, health, and safety are prime examples of social challenges that can be addressed through sustainable innovation (**Albareda and Hajikhani, 2019**).

Sustainable innovation has implications for social, technological, and cultural aspects of supply chains, which can bring about performance improvement in various organizational and market aspects (**Tariq et al., 2017**). The SSCM scholars have long acknowledged that innovation plays a critical role in long-term sustainable development, investigating sustainable innovation in various domains, like in smart product design **(Yin et al., 2020)**, and end-user sustainable innovation **(Nielsen, 2020)**, and policymaking **(Veldhuizen, 2020)**. Overall, sustainable innovation consists of social, economic, and environmental aspects (**Gupta et al., 2020**); **Figure 1** illustrates the key dimensions of sustainable innovation, which are intertwined and may have overlapped. Social innovation, as the focus of the present study, is reviewed in the upcoming sub-section.

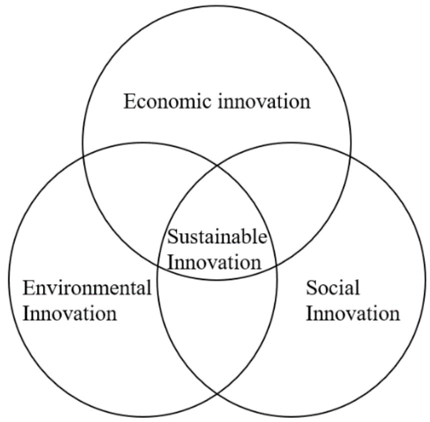

Figure 1. Dimensions of sustainable innovation.

2.3. Social innovation and the COVID-19 pandemic

Social innovations are new ideas with system-changing nature to deal with socio-economic and -environmental aspects and influence people's understanding (**Pol and Ville, 2009**). In another definition, social innovation is described as novel social practices for dealing with various social challenges **(Howaldt and Kopp, 2012)**; it consists of implementing novel ideas to resolve different socio-environmental issues, improve sustainability, and pursue sustainable development goals (**Ramani et al., 2017**). **McKelvey and Zaring (2018)** suggested that social innovation is a major driver for pursuing social changes; it can be implemented in various domains, like commercial, non-profit, and government companies to offer innovative solutions to various socio-environmental problems **(Saji and Ellingstad, 2016)**. Companies can establish a competitive advantage and enhance profitability by creating social values by implementing social innovative practices **(Ozdemir et al., 2017)**.

The COVID-19 pandemic is, by far, the most disruptive event of the past century. The pandemic has seriously impacted humanity and negatively impacted the world economy and the global market (**Remko, 2020; Sarkis et al., 2020**). In particular, supply chains have suffered from serious damage to brand image, supply continuity, stakeholder safety, and logistic services, which have resulted in various levels of performance degradation (**Govindan et al., 2020**). Arguing that industry experts are concerned the most with the damaging impacts of the COVID-19 situation on business activities and supply chains, **Gostin and Wiley (2020)** noted that companies are confronting challenges pertinent to social and environmental aspects through practical and innovative solutions. In this situation, corporations have employed different social initiatives, like health-related factors, working in remote conditions, skill improvement, and other safety-related measures to reduce the adverse impacts of the pandemic on supply chains (**Majumdar et al., 2020**). **Table 1** summarizes various social innovation factors, including both conventional social innovation considerations, and those pertinent to the COVID-19 pandemic.

Table 1. Social innovation factors from the literature.

Factors	Supporting References
Efficient communication strategies in healthcare	**Sharma et al. (2020); McKelvey and Zaring (2018)**
Improving skills	**Sharma et al. (2020); Gostin and Wiley (2020)**
Cultural and social principles	**Koberg and Longoni (2019); Jain and Singh (2020)**
Responding to social pressures of stakeholders	**Tariq et al. (2017); Abdel-Basset and Mohamed (2020)**
Sharing awareness	**Majumdar et al. (2020); Govindan et al. (2020)**
A diversified portfolio of suppliers	**Majumdar et al. (2020); Govindan et al. (2020)**
Occupational health and safety	**Zhu et al. (2018); Chen et al. (2020)**
Localization	**Sarkis et al. (2020); Remko (2020)**
Corporate social responsibility initiatives	**Gupta et al. (2020); Ozdemir et al. (2017)**
Working in remote situations	**Sarkis et al. (2020); Gostin and Wiley (2020)**
Implementing social and economic initiatives	**Govindan et al. (2016); Tariq et al. (2017)**
Utilizing practical policies considering social indicators	**Jain and Singh (2020); Chen et al. (2020)**

2.4. Research gap

Howaldt and Kopp (2012) suggested that social innovation should receive more attention relative to technological innovation to deal with social issues. Social innovation has received recent recognition both in the academic literature and practice, with a growing number of scholars investigating the social aspect of sustainability innovation from different perspectives, like cross-country comparison of social innovations for sustainable consumption **(Schäfer et al., 2020)**, food provisioning **(Cattivelli and Rusciano, 2020)**, public health **(Chui and Ko, 2021)**, universities and social innovation for global sustainable development **(Arocena and Sutz, 2020)**, digital eco-system **(Rodrigo and Palacios, 2020)**, telecommunication and financial services **(Babu et al., 2020**), forestry **(Ludvig et al., 2020)**, as well as conceptual studies for general application **(Farzad et al., 2020; Li, 2021).** Studies at the intersection of social innovation, sustainable supply chains, and the COVID-19 pandemic are very limited.

A growing number of studies have shifted their focus on exploring the impact of the pandemic situation on various aspects of SSCM (e.g., **Sarkis et al., 2020; Ivanov, 2020; Queiroz et al., 2020)**. Fewer studies explored social innovation decision factors at the intersection of supply chain and COVID-19 topics (**Govindan et al., 2020**). To the best of the authors' knowledge, the mutual influence among social innovation factors considering the pandemic situation has not been studied. This study extends to address this gap by developing a decision support tool to analyze the interdependencies among social innovation factors, which helps understand the underpinnings of this aspect of sustainable innovation. A detailed description of the developed method is provided in the next section.

3. Research methodology

This section introduces the Rough-Z-DEMATEL approach. The Rough-Z-DEMATEL improves the adaptability of the basic fuzzy DEMATEL by effective integration of the expert's opinions/judgments and the confidence of experts in the assessment as well as addressing the uncertainty of information (**Lo et al., 2019**). The basic concepts and operators of the Z fuzzy set and rough numbers are first presented. Next, the computational steps of the Rough-Z-DEMATEL approach are detailed. Finally, the Influential Network Relation Map (INRM) is described for the visualization of the interrelationships between the studied factors.

3.1. Z fuzzy set

In group decision-making, the confidence of the decision-makers/experts in the assessment and the uncertainty of information should be taken into consideration. **Zadeh (2011)** proposed Z-numbers as a special type of fuzzy method that measures the confidence of experts in the evaluation. Z-numbers have been widely used in various decision-making problems (**Tian et al., 2020**, **Chutia, 2021**) to address these issues. The computational process of Z-numbers is detailed below.

Step 1. *Define the fuzzy system of the evaluation value and confidence*

Z-numbers are modeled considering triangular fuzzy triplets. A Z-number can be defined as $Z = \left(\tilde{F}, \tilde{Q}\right) = \left(\left(f^L, f^M, f^U\right), \left(q^L, q^M, q^U\right)\right)$, where $\tilde{F}$ represents the fuzzy membership function of general evaluation, namely $\tilde{F} = \left(f,\ \mu_{\tilde{F}}\right) \middle| y \in [0,\ 1]$, and $\tilde{Q}$ is the confidence level of the expert in the evaluation that is also a fuzzy membership function denoted by $\tilde{Q} = \left(q,\ \mu_{\tilde{Q}}\right) \middle| y \in [0,\ 1]$.

Step 2. *Convert the fuzzy membership function of confidence to the crisp equivalent*

The confidence $\tilde{Q}$ is converted into a crisp value by applying the integral concept shown in **Equation (1)**. The parameter "φ" denotes the confidence weight.

$$\varphi = \frac{\int^{y} \mu_{\tilde{Q}} \, dy}{\int^{\mu_{\tilde{Q}}} dy}. \tag{1}$$

Step 3. *Generate a Z-number*

Incorporate the confidence weight φ into the evaluation value $\tilde{F}$ to obtain the weighted Z fuzzy membership function using **Equation (2)**.

$$Z^{\varphi} = \left\{ \left(y,\ \mu_{\tilde{F}^{\varphi}} \right) \middle| \mu_{\tilde{F}^{\varphi}}\left(y \right) = \varphi \mu_{\tilde{F}}\left(y \right),\ y \in \left[0,1\right] \right\}. \tag{2}$$

Finally, the weighted Z fuzzy membership function can be converted into a regular triangular fuzzy number using **Equation (3)**.

$$Z^{*} = \left(\sqrt{\varphi} f^{L}, \sqrt{\varphi} f^{M}, \sqrt{\varphi} f^{U} \right). \tag{3}$$

3.2. Rough numbers

In group decision-making, the alternative rankings/priorities are determined based on multiple experts' integrated subjective assessments. That is, observations/opinions/judgments, the survey data of multiple experts should be integrated in a meaningful way to improve the decision outcomes (**Yazdani et al., 2020**). **Zhai et al. (2008)** developed rough numbers to construct the upper and lower approximations of a group opinion based on the rough set theory. The implementation process of rough numbers is briefed below.

Step 1. *Construct lower and upper approximation*

Assuming U as a universe containing all objects with X being a random object from U, there exists a set construct with v classes denoting the expert's preferences, $E = \{K_1, K_2, \ldots, K_v\}$ where $K_1 < K_2$

$<\ldots< K_v$. In this definition, if $\forall X \in U$, $K_q \in E$, $1 \le q \le v$, two sets $\underline{Apr}(K_q)$ and $\overline{Apr}(K_q)$ represent the lower and upper approximations of K_q, which are represented in **Equations (4)** and **(5)**, respectively. Besides, the boundary interval, denoted by $Bnd(K_q)$ can be determined using **Equation (6)**.

$$\underline{Apr}(K_q) = \{X \in U / E(X) \le K_q\}, \text{ the lower approximation;} \quad (4)$$

$$\overline{Apr}(K_q) = \{X \in U / E(X) \ge K_q\}, \text{ the upper approximation;} \quad (5)$$

$$Bnd(K_q) = \{X \in U / E(X) \ne K_q\} = \{X \in U / E(X) > K_q\} \cup \{X \in U / E(X) < K_q\}. \quad (6)$$

Step 2. *Define rough lower and upper limits*

The expert opinions can be aggregated using rough numbers with lower and upper limits, i.e. $\underline{Lim}(K_q)$ and $\overline{Lim}(K_q)$. These limits are calculated using the arithmetic mean of the elements in the lower and upper approximations shown in **Equations (7)** and **(8)**, respectively.

$$\underline{Lim}(K_q) = \sum_{i=1}^{N_L} E(X) / N_L \left| X \in \underline{Apr}(K_q) \right.; \quad (7)$$

$$\underline{Lim}(K_q) = \sum_{i=1}^{N_L} E(X) / N_U \left| X \in \underline{Apr}(K_q) \right.. \quad (8)$$

where N_L and N_U indicate the total number of objects contained in the lower and upper approximations of K_q, respectively. Notably, the rough boundary, $RBnd(K_q)$ represents the interval between the upper and lower limits of object K_q, as shown in **Equation (9)**.

$$RBnd(K_q) = \overline{Lim}(K_q) - \underline{Lim}(K_q). \quad (9)$$

$RBnd(K_q)$ represents the calculated value of expert consensus, with higher values indicating that there are variations in the experts' opinions while lower $RBnd(K_q)$ shows that the experts unanimously agree without major conflicts in their judgments.

Step 3. *Determine the interval value of rough numbers*

As a final step, the opinions of a group of experts should be converted into a set of rough numbers shown in **Equation (10)**. For a detailed explanation of the calculation of rough numbers, we refer the readers to **Chang et al. (2019)**.

$$RN\left(K_q\right)=\left[\underline{Lim}\left(K_q\right),\overline{Lim}\left(K_q\right)\right] \quad (10)$$

3.3. The proposed technique: Rough-Z-DEMATEL

As one of the most popular Multiple Criteria Decision-Making (MCDM) techniques, DEMATEL evaluates the interrelationship between criteria or factors. The outcome of DEMATEL analysis is a structured visual graph, the INRM, which helps decision-makers or experts to understand the direction of influence between the factors (**Gul, 2019**).

This study extends the DEMATEL technique by integrating (1) Z-numbers to reflect the qualitative information uncertainty and individual confidence of experts in the evaluation; (2) rough set theory to aggregate interview data from multiple experts. Rough-Z-DEMATEL not only improves the coverage of uncertain information but also determines the consensus of a group of decision-makers. We now elaborate on the computational procedure of the Rough-Z-DEMATEL.

Step 1. *Prepare the list of social sustainability innovation factors*

Invite professional experts on social sustainable innovation to set up an expert group. After group discussion and literature review, the evaluation factors, $F_i=\{F_1,\ F_2,\ldots,\ F_n\}$ are determined.

Step 2. *Create the fuzzy membership function of Z-numbers*

The Z membership functions across MCDM methods are different. This study adopts the Z-DEMATEL linguistic variables proposed by **Hsu et al. (2021)**. For evaluating the interrelationships between factors, the experts determine the influence of factor *i* on factor *j*, (*i*, *j*

=1, 2,…, *n),* and assign their confidence in the response. The influence evaluation scale is determined using one of the following linguistic terms: "No Influence (NI)", "Weak Influence (WI)", "Fair Influence (FI)", "Very high Influence (VI)", and "Absolute Influence (AI)". Besides, the five scales of confidence are "Very Low (VL)", "Low (L)", "Moderate (M)", "High (H)", and "Very High (VH)". For example, an expert's response to assessing an event is "weak influence and moderate confidence." It can be recorded as {WI, M}. That is, the corresponding Z membership function is (0.000, 0.707, 1.414). Given a total of 25 combinations of linguistic terms, the Z fuzzy membership function corresponding to the linguistic variable of each combination is provided in **Table 2**.

Table 2. The linguistic variables and Z membership functions (**Hsu et al. 2021)**

		Confidence				
		VL	L	M	H	VH
Influence	*NI*	(0.000, 0.000, 0.316)	(0.000, 0.000, 0.548)	(0.000, 0.000, 0.707)	(0.000, 0.000, 0.837)	(0.000, 0.000, 0.949)
	WI	(0.000, 0.316, 0.632)	(0.000, 0.548, 1.096)	(0.000, 0.707, 1.414)	(0.000, 0.837, 1.673)	(0.000, 0.949, 1.897)
	FI	(0.316, 0.632, 0.949)	(0.548, 1.096, 1.644)	(0.707, 1.414, 2.121)	(0.837, 1.673, 2.510)	(0.949, 1.897, 2.846)
	VI	(0.632, 0.949, 1.265)	(1.096, 1.644, 2.192)	(1.414, 2.121, 2.828)	(1.673, 2.510, 3.347)	(1.897, 2.846, 3.795)
	AI	(0.949, 1.265, 1.265)	(1.644, 2.192, 2.192)	(2.121, 2.828, 2.828)	(2.510, 3.347, 3.347)	(2.846, 3.795, 3.795)

Step 3. *Establish the Z direct influence matrix for each expert*

The experts use the linguistic variables in **Table 2** to construct a direct influence matrix, as shown in **Equation (11)**.

$$\otimes \boldsymbol{D}^{(k)} = \left[\otimes d_{ij}^{(k)}\right]_{n\times n} = \begin{bmatrix} \otimes d_{11}^{(k)} & \otimes d_{12}^{(k)} & \cdots & \otimes d_{1n}^{(k)} \\ \otimes d_{21}^{(k)} & \otimes d_{22}^{(k)} & \cdots & \otimes d_{2n}^{(k)} \\ \vdots & \vdots & \ddots & \vdots \\ \otimes d_{n1}^{(k)} & \otimes d_{n2}^{(k)} & \cdots & \otimes d_{nn}^{(k)} \end{bmatrix}_{n\times n}. \tag{11}$$

where $\otimes d_{ij}^{(k)} = \left(d_{ij}^{(k),L},\ d_{ij}^{(k),M},\ d_{ij}^{(k),U}\right)$ represents a Z-number. It is worthwhile noting that the diagonal elements in the matrix are 0 (i.e., there is no self-influence); that is, $\otimes d_{ii}^{(k)} = 0$ when $i = j$.

Step 4. *Defuzzying the elements of Z direct influence matrix*

Equation (12) is used to defuzzify the elements in the direct relationship matrix.

$$d_{ij}^{(k)} = \frac{\left(d_{ij}^{(k),L} + 2\cdot d_{ij}^{(k),M} + d_{ij}^{(k),U}\right)}{4}. \tag{12}$$

Step 5. *Generate the rough direct influence matrix*

Applying the calculation process of rough numbers in **Section 3.2**, the direct influence matrix from the experts is integrated into one rough direct influence matrix shown in **Equation (13)**.

$$RN(\boldsymbol{D}) = \left[RN\left(d_{ij}\right)\right]_{n\times n} = \begin{bmatrix} RN(d_{11}) & RN(d_{12}) & \cdots & RN(d_{1n}) \\ RN(d_{21}) & RN(d_{22}) & \cdots & RN(d_{2n}) \\ \vdots & \vdots & \ddots & \vdots \\ RN(d_{n1}) & RN(d_{n2}) & \cdots & RN(d_{nn}) \end{bmatrix}_{n\times n}. \tag{13}$$

where $RN\left(d_{ij}\right) = \left[\underline{Lim}\left(d_{ij}\right), \overline{Lim}\left(d_{ij}\right)\right]$ and symbol "*RN*" represents a rough number.

Step 6. *Calculate the normalized rough direct relation matrix*

Equation (14) is used to normalize the rough direct influence matrix.

$$RN(\boldsymbol{A}) = \left[RN(a_{ij})\right]_{n\times n} = \begin{bmatrix} \rho\cdot RN(d_{11}) & \rho\cdot RN(d_{12}) & \cdots & \rho\cdot RN(d_{1n}) \\ \rho\cdot RN(d_{21}) & \rho\cdot RN(d_{22}) & \cdots & \rho\cdot RN(d_{2n}) \\ \vdots & \vdots & \ddots & \vdots \\ \rho\cdot RN(d_{n1}) & \rho\cdot RN(d_{n2}) & \cdots & \rho\cdot RN(d_{nn}) \end{bmatrix}_{n\times n} \tag{14}$$

where $RN(a_{ij}) = \left[\underline{Lim}(a_{ij}), \overline{Lim}(a_{ij})\right]$, and $\rho = \min\left\{\frac{1}{\max_i \sum_{j=1}^{n} \overline{Lim}(a_{ij})}, \frac{1}{\max_j \sum_{i=1}^{n} \overline{Lim}(a_{ij})}\right\}$.

Step 7. *Obtain the rough total influence matrix*

The rough total influence matrix is raised to an infinite power, as shown in **Equation (15)** to estimate the total influence between the factors, which consists of direct and indirect relationships. **Equation (15)** is derived from **Equation (16)** as a simplified calculation formula.

$$RN(\boldsymbol{T}) = RN(\boldsymbol{A}) + RN(\boldsymbol{A})^2 + \cdots + RN(\boldsymbol{A})^\infty \tag{15}$$

$$\begin{aligned} RN(\boldsymbol{A}) &= RN(\boldsymbol{A}) + RN(\boldsymbol{A})^2 + \cdots + RN(\boldsymbol{A})^\infty = RN(\boldsymbol{A})\left(\boldsymbol{I} + RN(\boldsymbol{A}) + RN(\boldsymbol{A})^2 + \cdots + RN(\boldsymbol{A})^{\infty-1}\right) \\ &= RN(\boldsymbol{A})\left(\boldsymbol{I} - RN(\boldsymbol{A})^\infty\right)\left(\boldsymbol{I} - RN(\boldsymbol{A})\right)^{-1} = RN(\boldsymbol{A})\left(\boldsymbol{I} - RN(\boldsymbol{A})\right)^{-1} \end{aligned} \tag{16}$$

where $RN(\boldsymbol{A})^\infty = [0]_{n\times n}$ and "$\boldsymbol{I}$" denotes the Identity matrix, which is a zero matrix with diagonal values of 1.

Step 8. *Plot INRM to visualize the influential relationship among the factors*

The degree of rough affecting relationship ($RN(R_i)$) and the degree of rough affected relationship ($RN(C_i)$) can be obtained by adding up the rough total influence matrix of every row and column, respectively, as shown in **Equations (17)- (18)**.

$$\left[RN(R_i)\right]_{n\times 1} = \left[\sum_{j=1}^{n} RN(t_{ij})\right]_{n\times 1}, \tag{17}$$

$$\left[RN\left(C_j\right)\right]_{1\times n}=\left[\sum_{i=1}^{n}RN\left(t_{ij}\right)\right]_{1\times n}=\left[RN\left(C_i\right)\right]_{n\times 1}^{T}. \tag{18}$$

where $RN\left(R_i\right)=\left[\underline{Lim}\left(R_i\right),\overline{Lim}\left(R_i\right)\right]$ and $RN\left(C_i\right)=\left[\underline{Lim}\left(C_i\right),\overline{Lim}\left(C_i\right)\right]$. On this basis, Equations **(19)- (20)** are used to convert the rough numbers into crisp equivalents denoted by R_i and C_i.

$$R_i=\frac{\left(\underline{Lim}\left(R_i\right)+\overline{Lim}\left(R_i\right)\right)}{2} \tag{19}$$

$$C_i=\frac{\left(\underline{Lim}\left(C_i\right)+\overline{Lim}\left(C_i\right)\right)}{2} \tag{20}$$

Finally, $R_i + C_i$ expresses the strength of total influences, comprising dispatched and received. Larger values of "$R_i + C_i$" for a factor determine its high significance in the evaluation system. Therefore, the influence weights of the factors can be obtained using **Equation (21)**.

$$w_i=\frac{\left(R_i+C_i\right)}{\sum_{i=1}^{n}\left(R_i+C_i\right)} \tag{21}$$

On the other hand, $R_i - C_i$ can be used to determine the net influence of the factor. Given $R_i + C_i$ and $R_i + C_i$ as the measures on the horizontal and vertical axis, respectively, the coordinates of each factor determine its position on INRM. Besides, arrows are used to show the direction of significant influence amongst every pair of factors.

4. Case application and results

4.1. Case background

Inputs from a developing country in the Middle East are used to explore the mutual influence among the social innovation factors during the COVID-19 pandemic. Social sustainability development in Iran's manufacturing sector is at its initial stages and needs more investment and investigation **(Ghadimi et al., 2017)**. For achieving the research objectives, seven managers from seven different Iranian manufacturing firms were selected as our experts to participate in this study and help in the assessment process. Each of these experts has more than 10 years of working experience. The experts are purposely selected from different backgrounds for gaining homogeneity and ensuring that the results can be generalized and inform other industry situations. According to **Rezaei et al. (2012)**, expert-based methodologies can rely on a small sample of experts, like **Gupta and Barua (2018)** and **Moktadir et al. (2020)**. **Table 3** summarizes the expert profiles.

Table 3. Profile of the experts involved in this study.

Expert	Position	Experience (Years)	Industry
1	Supply manager	15	Leather manufacturing firm
2	Production manager	16	Steel manufacturing firm
3	Financial manager	17	Automobile firm
4	General manager	12	Electronic firm
5	Purchasing manager	11	Tile firm
6	Assistant supply manager	15	Plastic firm
7	Marketing Manager	18	Motorcycle firm

4.2. The assessment framework

Given the social innovation factors in **Table 1**, a survey was designed and submitted to the experts to determine whether these factors are perceived as relevant in their company's supply chains; (Yes) for accepted, or (No) for rejected. Besides, they were asked to suggest additional social innovation factors that are perceived as relevant according to their experience. After approving the factors list by at least five experts, it was sent back to the experts for the next round of review, and they were requested to revise their first response if necessary. On this basis, '*Rights of the employees*' and '*Quick response to market demand for sustainable products*' were suggested by two of the decision-makers. After three rounds of reviews, eight factors were selected for the final evaluation, as explained in **Table 4**. This screening approach has been widely applied to determine whether a particular factor should be included in the final assessment **(Ahmadi et al., 2021)**.

Table 4. Decision support framework of the study.

Factors	**Explanation**
Utilizing practical policies considering social indicators (*F 1*)	This relates to the utilization of effective strategies and programs taking into consideration social dimension of sustainability.
Efficient communication strategies in healthcare (*F 2*)	This relates to the employing effective communication policies during the COVID-19 pandemic.
Cultural and social principles (*F 3*)	The cultural and social values within a company determine the way the employees behave in unprecedented conditions; adjusting such values facilitate organizational sustainability and resilience.
Improving skills (*F 4*)	Improving the workforce skills and preparing them to better deal with the challenges in turbulent situations.
Rights of the employees (*F 5*)	Workforce rights at the workplace and improving the working conditions sustainably.
Quick response to market demand for sustainable products (*F 6*)	Developing knowledge about the market dynamics, timely response to demand changes, and introducing sustainable products/services.
Working in remote situations (*F 7*)	Understanding the workforce issues related to remote working conditions during COVID-19 outbreak; this includes soft and hard factors that impact the health, wellness, and productivity of the employees.
Localization (*F 8*)	Offering more opportunities to locals and more reliance on the native capacity.

4.3. Application of Rough-Z-DEMATEL technique to the case

The experts were invited to assess the mutual influence of factors using the linguistic terms from **Table 2**. The input from Expert 1is presented in **Table 5** as an example. Following the Z-numbers conversion approach proposed by **Hsu et al. (2021)**, the elements of **Table 5** are then converted to Z membership function equivalents shown in **Table 6**. Finally, the defuzzification procedure is applied to the Z membership functions to obtain the crisp direct influence matrix of Expert 1, as shown in **Table 7**. At the pre-processing stage, the uncertainty and confidence of all experts are considered in the assessment.

Table 5. The Z direct influence matrix of Expert 1 (linguistic terms).

	F1	F2	F3	F4	F5	F6	F7	F8
F1	0	(FI, H)	(FI, H)	(VI, M)	(FI, M)	(VI, H)	(FI, H)	(FI, H)
F2	(VI, H)	0	(VI, H)	(WI, M)	(FI, M)	(FI, H)	(WI, M)	(WI, H)
F3	(FI, VH)	(WI, M)	0	(NI, M)	(WI, VH)	(WI, VH)	(NI, H)	(WI, H)
F4	(VI, M)	(FI, M)	(VI, M)	0	(VI, VH)	(WI, VH)	(NI, M)	(VI, VH)
F5	(WI, M)	(NI, VH)	(WI, H)	(FI, VH)	0	(NI, M)	(VI, VH)	(VI, VH)
F6	(NI, H)	(VI, VH)	(FI, H)	(VI, H)	(VI, H)	0	(VI, VH)	(FI, VH)
F7	(VI, H)	(VI, VH)	(NI, VH)	(AI, H)	(AI, H)	(VI, M)	0	(NI, H)
F8	(WI, VH)	(WI, H)	(WI, VH)	(VI, H)	(WI, H)	(AI, VH)	(AI, H)	0

Table 6. The Z direct influence matrix of Expert 1 (Z membership functions).

	F1	F2	F3	F4	F5	F6	F7	F8
F1	0	(0.837, 1.673, 2.510)	(0.837, 1.673, 2.510)	(1.414, 2.121, 2.828)	(0.707, 1.414, 2.121)	(1.673, 2.510, 3.347)	(0.837, 1.673, 2.510)	(0.837, 1.673, 2.510)
F2	(1.673, 2.510, 3.347)	0	(1.673, 2.510, 3.347)	(0.000, 0.707, 1.414)	(0.707, 1.414, 2.121)	(0.837, 1.673, 2.510)	(0.000, 0.707, 1.414)	(0.000, 0.837, 1.673)
F3	(0.949, 1.897, 2.846)	(0.000, 0.707, 1.414)	0	(0.000, 0.000, 0.707)	(0.000, 0.949, 1.897)	(0.000, 0.949, 1.897)	(0.000, 0.000, 0.837)	(0.000, 0.837, 1.673)
F4	(1.414, 2.121, 2.828)	(0.707, 1.414, 2.121)	(1.414, 2.121, 2.828)	0	(1.897, 2.846, 3.795)	(0.000, 0.949, 1.897)	(0.000, 0.000, 0.707)	(1.897, 2.846, 3.795)
F5	(0.000, 0.707, 1.414)	(0.000, 0.000, 0.949)	(0.000, 0.837, 1.673)	(0.949, 1.897, 2.846)	0	(0.000, 0.000, 0.707)	(1.897, 2.846, 3.795)	(1.897, 2.846, 3.795)
F6	(0.000, 0.000, 0.837)	(1.897, 2.846, 3.795)	(0.837, 1.673, 2.510)	(1.673, 2.510, 3.347)	(1.673, 2.510, 3.347)	0	(1.897, 2.846, 3.795)	(0.949, 1.897, 2.846)
F7	(1.673, 2.510, 3.347)	(1.897, 2.846, 3.795)	(0.000, 0.000, 0.949)	(2.510, 3.347, 3.347)	(2.510, 3.347, 3.347)	(1.414, 2.121, 2.828)	0	(0.000, 0.000, 0.837)
F8	(0.000, 0.949, 1.897)	(0.000, 0.837, 1.673)	(0.000, 0.949, 1.897)	(1.673, 2.510, 3.347)	(0.000, 0.837, 1.673)	(2.846, 3.795, 3.795)	(2.510, 3.347, 3.347)	0

Table 7. The crisp direct influence matrix of Expert 1 (defuzzification results).

	F1	F2	F3	F4	F5	F6	F7	F8
F1	0	1.673	1.673	2.121	1.414	2.510	1.673	1.673
F2	2.510	0	2.510	0.707	1.414	1.673	0.707	0.837
F3	1.897	0.707	0	0.177	0.949	0.949	0.209	0.837
F4	2.121	1.414	2.121	0	2.846	0.949	0.177	2.846
F5	0.707	0.237	0.837	1.897	0	0.177	2.846	2.846
F6	0.209	2.846	1.673	2.510	2.510	0	2.846	1.897
F7	2.510	2.846	0.237	3.138	3.138	2.121	0	0.209
F8	0.949	0.837	0.949	2.510	0.837	3.558	3.138	0

MCDM studies predominantly use simplistic methods, like simple and weighted averages to integrate group judgments. This approach is limited in that it may cause missing parts of the information. For example, even if an expert expresses extreme opinions, they can be ignored when the average method is used. The concept of rough set theory is applied to address this issue. **Table 8** shows the outcome that is used to construct the lower and upper approximations of the group. In so doing, the consensus of experts can be subtracted from the upper approximation by the lower approximation. For example, the rough direct influence of F1 on F2 is [1.682, 1.792] and the consensus degree in this judgment amounts to 0.11. Given the maximum and minimum values in **Table 2**, the consensus degree ranges from 0 to 3.795.

Table 8. The rough direct influence matrix (the integrated judgments of the experts).

	F1	F2	F3	F4	F5	F6	F7	F8
F1	[0, 0]	[1.682, 1.792]	[1.074, 2.052]	[1.458, 2.016]	[0.685, 1.468]	[1.009, 2.571]	[0.532, 1.614]	[0.776, 2.265]
F2	[0.607, 1.787]	[0, 0]	[1.518, 2.588]	[0.785, 1.886]	[0.7, 1.613]	[1.278, 2.266]	[0.697, 1.421]	[0.583, 1.756]
F3	[1.487, 2.308]	[0.781, 1.919]	[0, 0]	[0.961, 2.35]	[0.938, 1.643]	[0.68, 2.104]	[0.92, 2.521]	[1.154, 2.029]
F4	[1.372, 2.244]	[0.807, 1.457]	[1.268, 2.359]	[0, 0]	[0.879, 2.185]	[0.86, 2.106]	[1.033, 2.353]	[1.343, 2.281]
F5	[0.568, 1.585]	[0.684, 2.344]	[0.689, 1.733]	[1.357, 2.271]	[0, 0]	[0.77, 2.429]	[1.909, 2.659]	[0.835, 2.386]
F6	[0.976, 2.304]	[1.067, 2.385]	[1.416, 2.088]	[1.084, 2.207]	[1.411, 2.532]	[0, 0]	[1.498, 2.459]	[1.337, 2.618]
F7	[0.997, 2.344]	[1.632, 2.547]	[0.845, 2.255]	[0.647, 1.959]	[1.855, 3.139]	[0.915, 2.264]	[0, 0]	[0.959, 2.218]
F8	[0.878, 1.934]	[0.576, 1.683]	[1.495, 2.66]	[0.679, 1.93]	[1.291, 2.262]	[1.261, 2.76]	[1.503, 2.359]	[0, 0]

After completing the computational process of Rough-Z-DEMATEL, the influence weights are obtained and the INRM is constructed considering the prominence ($R_i + C_i$), and net-causation ($R_i - C_i$) values. According to **Table 9**, F6 has the highest influence weight, which is 0.135. There is no significant difference in the weight of the rest of the factors because they have a strong mutual influence. The INRM of the factors is presented in **Figure 1** followed by a discussion of the results provided in **Section 5**.

Table 9. The results of the Rough-Z-DEMATEL analysis.

	Rough R	Rough C	R	C	R+C	R-C	weight	Rank
F1	[0.786, 10.679]	[0.758, 11.185]	5.733	5.971	11.704	-0.239	0.118	7
F2	[0.683, 10.321]	[0.792, 10.926]	5.502	5.859	11.362	-0.357	0.114	8
F3	[0.759, 11.425]	[0.898, 11.982]	6.092	6.440	12.532	-0.348	0.126	4
F4	[0.827, 11.536]	[0.764, 11.248]	6.181	6.006	12.188	0.175	0.123	6
F5	[0.753, 11.834]	[0.850, 11.441]	6.294	6.145	12.439	0.148	0.125	5
F6	[0.953, 12.577]	[0.742, 12.501]	6.765	6.622	13.387	0.143	0.135	1
F7	[0.849, 12.642]	[0.882, 11.810]	6.745	6.346	13.091	0.399	0.132	2
F8	[0.843, 11.974]	[0.767, 11.895]	6.409	6.331	12.739	0.078	0.128	3

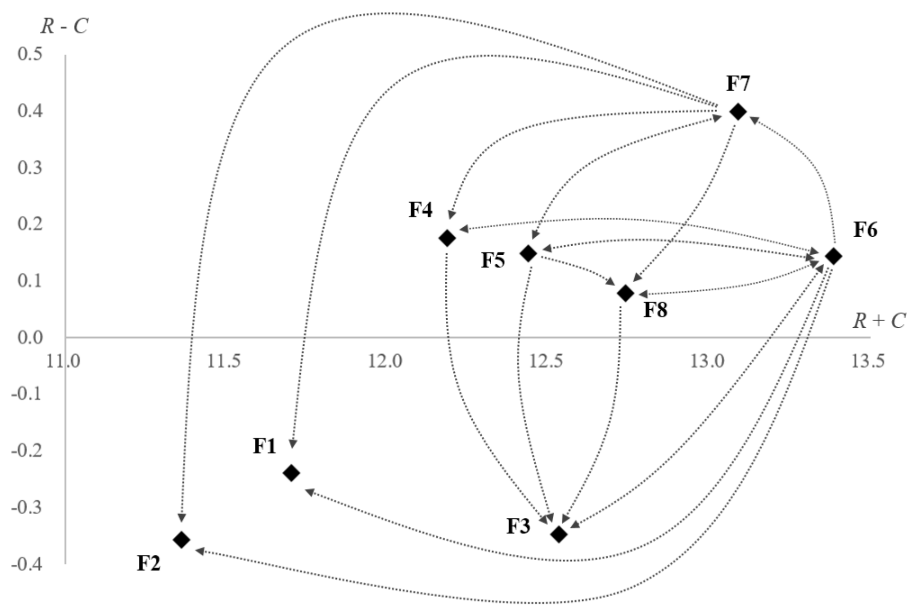

Fig. 1. The influential network relation map of the factors.

5. Discussions

The resulting ranking of social sustainability innovation factors is F6 > F7 > F8 > F3 > F5 > F4 > F1 > F2; "Quick response to market demand for sustainable products (F6)" received the highest ranking in the analysis, hence, can be regarded as the most influential factor for attaining social sustainability innovation. Previous studies suggested that corporations should develop effective strategies and consider a variety of social standards while responding to market demands (**Ahmadi et al., 2020**). Particularly in highly uncertain situations, like the COVID-19 pandemic, applying effective social standards plays a significant role in maintaining the sustainability and competitiveness of corporations (**Tariq et al., 2017**). This is in line with our findings from the Rough-Z-DEMATEL analysis where "Quick response to market demand for sustainable products" shows the highest prominence. Industrial experts and decision-makers in emerging economies should prioritize this factor to pursue social sustainability innovation during and after the COVID-19 pandemic.

The next important social sustainability innovation factor appears to be 'Working in remote situations (F7)' considering the prominence ranking. During the COVID-19 pandemic, most the employees are working from home, some of whom may face technical issues related to infrastructure and bandwidth ability and limitations, like living with families in a small homes with limited facilities. Employers need to understand the situation of the employees and provide them with the necessary support and solutions to their problems to ensure that they are more effectively engaged in work and can stay productive. Besides, working from home may become a norm for certain industries. The results are in line with the findings of **Gostin and Wiley (2020)** who also indicate that employers need to focus on the working conditions of their employees during the time of the pandemic.

The third important factor as per the prominence ranking is 'Localization (F8)'. The pandemic has caused disruptions all over the world and impacted the logistics sector the most with production schedules being delayed for many organizations. Besides, many small- and medium-sized organizations have been forced to close down or limit their operations, causing job losses. To overcome the impact of disruptions caused by major disruptive events, like pandemics, organizations need to be more supportive of local companies and products, while organizations need to source more products and raw materials from local suppliers and small businesses, which in turn improves employment opportunities for locals **(Sarkis et al., 2020; Pourhejazy and Ashby, 2021)**.

The 'Cultural and social principles (F3)' is the next important social innovation factor. Organizations all over the world are disrupted due to the pandemic while their employees' well-being and productivity are also in jeopardy. Organizations need to develop and re-assess their cultural and social values and principles to deal with changing situations. Managers should focus on developing transparency and open communication within the organizations and creativity among employees to enhance problem-solving capabilities. Besides, they should establish a collaborative work environment for engaging employees at all functional levels for developing solutions to the problems the company faces. Overall, developing a culture that value and promote innovation in the organizations encourages employees to come up with novel solutions to deal with the disruptions caused due to pandemic. Recent studies, like **(Koberg and Longoni, 2019)** and **(Jain and Singh, 2020)** support the idea that organizations need to focus on their cultural and social values for supporting social sustainable innovations for dealing with the impacts of the pandemic.

Analyzing the INRM graph in **Figure 1**, one can conclude that the social sustainability innovation factors ‘Quick response to market demand for sustainable products (F6)’, ‘Working in remote situations (F7)’, ‘Localization (F8)’, ‘Rights of the employees (F5)’ and ‘Improving skills (F4)’ have emerged as cause group factors (i.e., the influencers). From the cause group factors, ‘Quick response to market demand for sustainable products (F6)’ has the highest influence in the network, which is also indicated by the prominence ranking. It is also observed that F6 influences every other social innovation factor. In this context, timely response to customer demands and knowing about sustainable products influences localization. As organizations aspire to quickly meet customer demand during the pandemic, they need to focus on developing more local sources for their product raw material and assemblies. These considerations together help enhance localization and offer employment opportunities to locals. F6 also strongly influences ‘Cultural and social principles (F3)’, ‘Improving skills (F4)’ and ‘Utilizing practical policies considering social indicators (F1)’. For companies to respond quickly to market changes, organizations should have a culture of open communication about the work that needs to be done in a certain time frame; this helps develop innovative solutions to meet the deadlines in the volatile scenario caused by the pandemic and other similar events. Besides, for adopting environmentally sustainable products and being responsive to customer needs in the time of the pandemic, organizations are encouraged to provide training to their employees to enhance their skills to meet the organizations’ goals during the pandemic. Devising policies and social sustainability initiatives are required to compete with other organizations during this volatile period, which emphasizes responsiveness and the launch of sustainable products during the pandemic as indicated by the interrelationship analysis.

The interrelationship analysis also revealed that ‘Working in remote situations (F7)’ has a significant influence on some other factors like ‘Improving skills (F4)’, ‘Efficient communication strategies in healthcare (F2)’, ‘Utilizing practical policies considering social indicators (F1)’, ‘Rights of the employees (F5)’, and ‘Localization (F8)’.

Four DEMATEL-based method comparisons, including original DEMATEL, triangular fuzzy DEMATEL, Z-DEMATEL, and Rough-Z-DEMATEL (our model) are considered to study the methodological implication of the proposed method. The first method is the classic DEMATEL, where the evaluation scale is from 0 to 4 to measure the interrelationship amongst the criteria. The second method is triangular fuzzy DEMATEL, which introduces triangular fuzzy numbers into DEMATEL to reflect information uncertainty. Z-DEMATEL is the third method, extending the concept of triangular fuzzy DEMATEL, which takes into account the confidence of experts in the evaluation. The last variant is the Rough-Z-DEMATEL technique, which is proposed in this paper. **Table 10** and **Figure 2** present the criteria weights and rankings for the four DEMATEL methods. The first two methods are not identical to the results of the proposed Rough-Z-DEMATEL analysis. Furthermore, although the results of Z-DEMATEL are similar to the proposed model, we consider the issue of expert integration more, and our information covers a larger range. **Table 11** summarizes a description of the differences between the four methods.

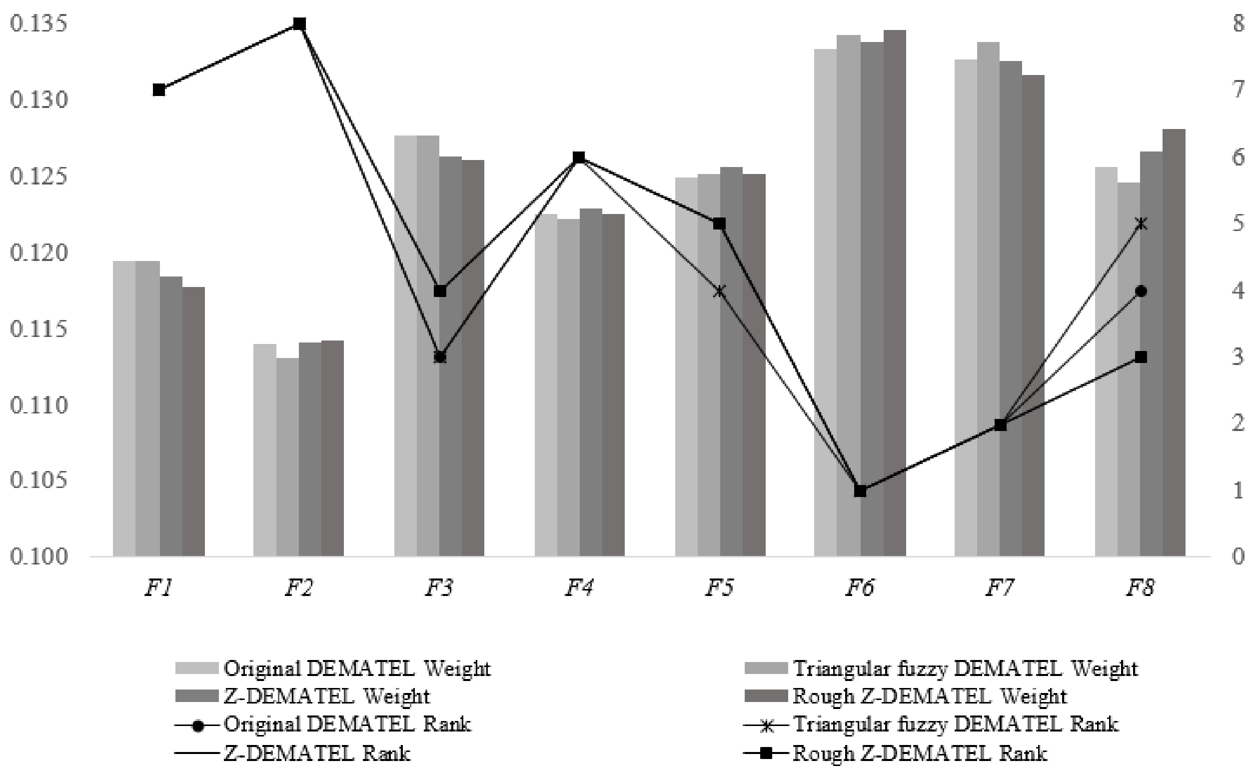

Fig. 2. The analysis results of the four methods comparison.

Table 10. Criteria weights and rankings for the four DEMATEL methods.

	Original DEMATEL		Triangular fuzzy DEMATEL		Z-DEMATEL		Rough Z-DEMATEL	
	Weight	Rank	Weight	Rank	Weight	Rank	Weight	Rank
F1	0.119	7	0.119	7	0.118	7	0.118	7
F2	0.114	8	0.113	8	0.114	8	0.114	8
F3	0.128	3	0.128	3	0.126	4	0.126	4
F4	0.122	6	0.122	6	0.123	6	0.123	6
F5	0.125	5	0.125	4	0.126	5	0.125	5
F6	0.133	1	0.134	1	0.134	1	0.135	1
F7	0.133	2	0.134	2	0.133	2	0.132	2
F8	0.126	4	0.125	5	0.127	3	0.128	3

Table 11. Difference comparison of four DEMATEL methods.

	Original DEMATEL	Triangular fuzzy DEMATEL	Z-DEMATEL	Rough Z-DEMATEL
Interaction relationship identification	✓	✓	✓	✓
Information uncertainty assessment		✓	✓	✓
Expert confidence measure			✓	✓
Multiple expert judgment integration				✓
Potential Information Coverage	Low	Medium	High	Very high

6. Implications

6.1 Practical implications

Given the limitations around working from home and the importance of providing technical support and infrastructure, having more employees working from remote locations influences an organization's ability to source raw materials and sub-assemblies of their products from local sources; in doing so, the issues related to the workforce can be alleviated and the market demand can be fulfilled in a timely fashion. In a post-pandemic world, the work-from-home experience opens cost-saving opportunities, support for less advantaged communities, and inclusion of vulnerable groups and people with special needs and disabilities. This requires organizations to provide training to their employees so that they can work from remote locations more effectively and efficiently considering available resources and without stress induced among employees because of the pandemic-like situations. Organizations are required to come up with policies for effective communication among employees working from different locations so that the organization's sustainability-related goals can be met effectively. Effective communication among employees helps them to come up with innovative and sustainable ideas for the problems and challenges that emerge due to pandemics. Finally, working from home as a paradigm shift requires fresh policies and law/regulatory frameworks to fully benefit from its advantages. The managers should also be cognizant of the fact that some workers can be more productive at home, and that an optimal combination of working from home and at the office in the post-pandemic world may be necessary. The pandemic experience should be used as an opportunity to build a stronger community that is better prepared for catastrophe. This topic should be investigated from the operations management, work psychology, and ergonomics perspectives.

6.2. Theoretical and Academic Implications

This study has some important theoretical and academic implications, this is the first study regarding exploring the influential relationship of social innovation factors during the COVID-19 pandemic. This study can act as a steppingstone for researchers and academicians to further explore other social factors under a different scenario. This study also acts as a reference for comparing social innovation factors during the pandemic and now after pandemic world, it will help researchers understand whether there is a shift in the importance of social innovation factors during both these scenarios. The results will also help the policymakers and decision makers in formulating policies for the future related to improving social innovation during a course of any disturbance like a pandemic. This study also applies Rough-Z-DEMATEL to explore the influential relationship of social innovation factors during the COVID-19 pandemic. This technique is also relatively new and taking a cue from this study, academicians and researchers can explore the possibility of application of this technique in other similar application areas.

7. Conclusions and future work

This study developed a decision analysis framework for investigating social innovation taking into consideration the COVID-19 pandemic situation, to analyze the interdependencies among the related factors in the manufacturing context of a developing country. Twelve social innovation factors were initially identified through a comprehensive review of the literature. After the screening by a group of seven industry experts, eight social innovation factors, including traditional and COVID-19-related considerations were considered for further evaluation. The Rough-Z-DEMATEL model was developed for exploring the interrelationships among social innovation factors within a novel group decision-making scheme. Notably, introducing the social innovation factors during the COVID-19 pandemic and developing the Rough-Z-DEMATEL technique for investigating the mutual influence among social innovation factors are the major academic contributions of this article. The practical contribution of this study comes from the insights provided into the understanding of the social dimension of sustainable innovation taking into account the COVID-19 pandemic situation. The outcomes of this study help managers make well-informed decisions.

There are certain limitations to this study, which can offer directions for further development in the field. The first limitation of this work is that few experts from manufacturing companies of one emerging economy have participated. Future works can consider other sectors and countries or regions considering comparing the findings with those of this manuscript. The second limitation of this work is that the decision support framework considers a limited number of factors. Potential future works could employ industry-specific factors and sub-factors for more accurate outcomes. Besides, this paper investigated only the social aspect of sustainable innovation during the COVID-19 disaster. The third suggestion for future works comes from extending our investigations to account for environmental and economic aspects of sustainable innovation under COVID-19 circumstances and exploring the interrelationships and possible interactions between them. For this purpose, other MCDM tools, like Interpretive Structural Modeling (ISM) can be extended by employing fuzzy or rough numbers to handle information ambiguity and uncertainty.

In so doing, the results could be compared with Rough-Z-DEMATEL to provide new insights. As the next suggestion for future research, the social innovation factors introduced in this study can inspire future studies on supply chains sustainability in times of major disasters. From a methodological perspective, future studies can integrate the stratified MCDM methods with DEMATEL or ISM to investigate the interrelationship among innovation factors considering uncertain situations and events that may happen in the future. Finally, social sustainability innovation research in developing countries is still in its early stages and requires more attention, especially in the era of the COVID-19 pandemic; this work can be considered a foundation for deeper studies on this research topic.

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