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# Decision-making model for AI adoption to achieve sustainable development goals in the context of developing countries

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The emergence of Artificial Intelligence (AI) and its increasingly broader impact across various sectors requires a comprehensive assessment of its effect on achieving the Sustainable Development Goals (SDGs). AI has immense potential to accelerate progress toward the SDGs, particularly in developing countries where challenges such as inadequate infrastructure, inequality, poverty, and environmental degradation persist. However, AI adoption in these regions poses unique challenges that require a tailored decision-making model to ensure equitable and sustainable outcomes. This research aims to identify the aspects that highly impact AI adoption, which will, in turn, contribute to achieving the SDGs. A systematic literature review was performed to define and determine the relative aspects, culminating in the proposal of a comprehensive decision-making model. The combined Fuzzy Decision-Making Trial and Evaluation Laboratory (FDEMATEL) and the Fuzzy Technique for Order Preference by Similarity to Ideal Solution (FTOPSIS) are used to classify interactions and rank these aspects. The result of the current study is based on the proposed decision-making model: Fuzzy DEMATEL-TOPSIS analysis revealed that aspects of the digital literacy divide, and shortage of skilled workforce from the social dimension is key aspects of AI adoption from the experts' perspective. The findings obtained from the proposed model could assist business organizations and policymakers in adopting and enhancing their decisions making prospects related to technology adoption for achieving SDGs. The findings and practical insights gained from this research could also help industry managers delve into the adoption, acceptance, and application of AI.

***Keywords:*** Decision-making model, AI adoption, Sustainable development, Fuzzy DEMATEL, Fuzzy TOPSIS

## 1. INTRODUCTION

The Sustainable Development Goals (SDGs) originated because of significant stakeholder consultation involving experts, policymakers, and institutions in 2015 as part of the 2023 agenda. The SDGs acted as a potent medium that which provided member states a viable development pathway ensuring balance between the social, economic, and environmental components of sustainable development [1]. It also helped to develop critical worldwide agreements and partnerships in areas such as gender inequality, poverty alleviation, social inclusion, sustainable cities, and climate change [2]. SDGs also offered a better framework with a broader reach than the Millennium Development Goals since they treated all countries equally: developed and developing alike, with countries free to implement and adopt it considering national priorities and circumstances [3]. In addition, SDGs provided a rare chance to regenerate global sustainability research and leveled the playing field for developing nations in the global development agenda [4].

To attain these goals, technology adoption would play a key role. According to research, Artificial Intelligence (AI) and machine learning can be crucial and play a critical role in achieving sustainable goals. In a developing country like India, 84% of industrial units are micro, small, and medium-sized businesses, which account for about 40% of total industrial production [2]. SDGs are vital for a nation's development as they provide momentum to a comprehensive and constructive framework to address the multi-faceted challenges in developing nations [3,5]. The requisite data can be received as outcomes in areas like eradication of poverty, education, health, gender equality, clean water facilities, and sustainable economic growth. In this regard, SDGs create a pathway towards the long-term prosperity and stability. This encourages the process of inclusive development, ensuring that all segments of society are benefitted from progress while fostering environmental sustainability and resilience to climate change. This strategy of all-encompassing not only the living standards of individuals but also strengthens the bases of strong institutions and partnerships, which are essential for sustained development and global cooperation.

Artificial Intelligence (AI) in the present scenario holds immense potential for driving progress and addressing key challenges in developing countries, but its adoption faces significant challenges [2]. One of the primary issues are inadequate digital infrastructure, including unreliable internet connectivity and frequent power outages, which hampers the deployment and effectiveness of AI technologies. In addition, the heightened costs associated with acquiring, implementing, and maintaining AI systems could be out-of-pocket for many developing nations, which often struggle to outshine with limited budgetary allocations and financial constraints. The digital literacy divide complicates further, as a significant portion of the population lacks the necessary skills to leverage AI tools effectively. This is exacerbated shortage of trained skilled professionals and local expertise in AI making it too difficult to develop, adapt, and sustain AI initiatives locally. Data scarcity and poor data quality are also critical issues as AI systems mostly depend on vast amounts of high-quality information to function accurately, and such data is often unavailable or unreliable in this case.

Yadav et al. [5] carried out a primary analysis of the efforts made by organizations in India to align sustainable goals as outlined in the Industry 4.0. Kar et al. [3] also noted that I4.0 may be a tool for adopting AI. Its intervention in the organizational functioning and practices determines straightforwardness and constitutes the organization's stability, sustainability, and ethics as a benchmark and foundation of businesses in developing nations. According to the experts, AI deployment for societal sustainability may have a greater impact and offer more promising products. As a result of this, there is a constant need to address both AI and SDGs. Policymakers and managers see AI as an important aspect of massive sustainable development. As a result, the authors thought that it would be a challenging one to investigate AI adoption to accelerate more sustainable development. The integration of AI with SDGs has garnered significant attention in contemporary research, highlighting AI's potential usage to accelerate progress towards these global objectives. AI can enhance data-driven decision-making, optimize resource allocation, and provide innovative solutions in various sectors that are crucial to sustainable development, such as healthcare, education, agriculture, and climate change. For instance, AI-driven predictive analytics can improve crop yields and food security by providing real-time insights to the farmers [6]. In the healthcare sector, AI algorithms can enhance disease diagnosis and management, thus improving health outcomes and reducing inequalities [7]. In addition, AI's capability in environmental monitoring helps in the effective management of natural resources and assists in mitigating the impacts of climate change [8].

However, the literature available underscores challenges, including ethical concerns, data privacy, and the need for robust regulatory frameworks to ensure equitable and sustainable AI deployment [8]. The ongoing research is critical to address current challenges and equip AI's potential to meet SDGs. In addition, organizations face many difficulties in visualizing the expected outcomes of AI technologies in decision-making. In a highly competitive environment, Multi-Criteria Decision Marking (MCDM) is one of the issues that decision-makers confront while adopting AI to achieve sustainable goals and improve quality standards. MCDM's required criteria could not be evaluated because the data obtained through assessments of decision-makers is inaccurate [6]. In addition, certain criteria can only be assessed subjectively [3]. Therefore, the demand for MCDM methods is significantly high.

The current model is developed for carrying research in this domain by integrating the Fuzzy Decision-Making Trail and Evaluation Laboratory (Fuzzy DEMATEL) and Fuzzy Order Preference through Ideal Solution (Fuzzy TOPSIS) approaches. This model is widely used to identify the critical aspects related to the adoption of AI by researchers [9]. Fuzzy DEMATEL is a powerful tool for assisting decision-makers in addressing complex problems involving multi-criteria decision-making and uncertainty. Therefore, this approach is used to determine the weights given to each aspect and the relative relevance of the various dimensions. In addition, a Fuzzy TOPSIS approach was used to rank and analyze discovered factors that are critical for AI adoption to meet the SDGs.

The focus of the prior research in this study is on "What are the aspects that impact the effectiveness of AI adoption within the developing countries?". Previous studies made attempts to identify and elaborate on the important aspects of AI adoption; their research primarily focused on technology adoption in a broader context and ignored model development. Therefore, this study provides key insights to aid decision-makers and government authorities in adopting AI-driven technology to derive solutions to critical problems. The contribution of the study is as follows:

We proposed a new AI adoption model that aligns with sustainability dimensions. Secondly, an intensive literature review was done with great precision on previous studies in the context of AI adoption in developed and developing nations to improve our understanding of the adoption aspects. The source of the data for the proposed model was the responses gathered from top-level decision-makers in industry and the government with expertise in technology import and development in developing countries. Thirdly, a new model was designed by using two MCDM methods, namely Fuzzy DEMATEL-TOPSIS, to analyze the data acquired from top-level experts who have been serving both in the industry and government sector. The resulting outcomes and insights gained through the observations could assist in strengthening the decision-makers in industry and government in their pursuit of excellence and efforts to promote the acceptance, adoption, and utilization of high-quality AI.

The rest of the paper is organized as follows: the next section presents a review of literature in the context of AI adoption and determined dimensions and its aspects. Section 3 illustrates the procedure for data collection and application of Fuzzy DEMATEL-TOPSIS methods, and findings are deliberated in Section 4. Research implications will be discussed in Section 5. This study's contribution and limitations are presented in Section 6 before references.

## 2. PRIOR RESEARCH

### 2.1 AI and sustainable development goals

The potential of AI integration in achieving SDGs was widely seen from the recent literature which emphasizes its significance across various sectors. In the field of the healthcare sector, AI intervention improves diagnostics, treatment, and delivers efficient healthcare delivery resulting in enhanced desired outcomes and reduced disparities [2,4,6]. In the agriculture field, precision farming and other AI-driven technologies assist farmers and subsidiary organizations in optimizing resources contributing to food security and sustainable agricultural practices [10]. AI also transforms education through supporting accessible and personalized learning experiences leading to inclusiveness and quality education [11]. Similarly, AI technologies help in environment management through better climate change mitigation, the development of disaster response strategies, and in conservation of natural resources [10]. However, the literature also underscores challenges, including data privacy concerns, digital divide, and algorithmic bias, which must be addressed to promote equitable and ethical AI development [12]. While AI offers significant opportunities to advance the SDGs, addressing associated challenges through comprehensive policies and ethical frameworks is key for maximizing its continuous positive impact on sustainable development.

### 2.2 AI adoption in developing countries

The growing body of literature on AI adoption highlights its transformative potential in addressing socio-economic challenges and advancing SDGs in developing countries. Research has shown that AI applications can enhance healthcare delivery, improve agricultural productivity, facilitate financial inclusion, and promote educational access among other areas. Liu. [14] emphasize the role of AI in improving efficiency and driving innovation in resource-constrained environments.

The current scenario reflects significant involvement of AI in the industrial sectors, which has gained momentum and is perceived as an affluent and reliant technological development for national growth. The Indian SMEs are often constrained by limited budgets and conventional technologies. Furthermore, SMEs are likely to face disadvantages due to a lack of adequate financial, human, and technological resources. Hence, these issues hinder the widespread adoption of AI significantly [5]. Moreover, numerous difficulties arise while adopting and implementing disruptive technologies [7]. To mitigate and counteract the adverse effects of disruptive technologies like AI, a collaborative association of industry and academia is a must to develop necessary technological progress, innovations and installing skill sets for SMEs. Besides this, the emergence of Industry 4.0 standards has increased AI's influence in the adoption process across industries [13]. However, significant barriers remain, including inadequate digital infrastructure, a shortage of skilled labor, ethical concerns regarding data privacy, and the risk of exacerbating existing inequalities [7]. Furthermore, many developing countries lack robust governance frameworks to ensure responsible AI adoption, leading to uneven distribution of benefits [2,8]. While existing literature often focuses on technological feasibility and policy recommendations, there is a critical research gap in developing holistic, context-specific decision-making model that address the socio-economic, ethical, and governance challenges unique to developing countries. This gap calls for more interdisciplinary studies that integrate local realities with global AI frameworks, ensuring that AI adoption supports equitable and sustainable development.

### 2.3 Identified factors for AI adoption

Over the years, many researchers have focused on exploring and identifying the critical dimension and significant factors that influence AI adoption specifically, in the developing nations context. The majority of the research has addressed economic problems and issues related to this topic [15]. However, investigation into factors and dimensions of social and environmental aspects in AI adoption is very limited. Hence, four distinct dimensions were considered in the present study: economic, social, environmental, and other. An exhaustive review of the literature on AI adoption has resulted in identifying the dimensions with its aspects, and these are listed in Table 1.

**Table 1. List of dimensions and aspects for AI adoption for SDGs.**

| Dimensions | Aspects | Definition | Input |
|---|---|---|---|
| Economic (D1) | (A1) High costs | The financial capacity of acquiring, implementing, and maintaining AI technologies can be prohibitive for many developing countries. | Singh et al.[2], Kar et al. [3] |
| | (A2) Economic inequality | There is a risk that AI adoption could exacerbate existing economic inequalities if benefits are not equitably distributed. | Farahani and Ghasemi [16], Abdallah [17] |
| | (A3) Funding and investment challenges | Securing consistent funding and investment for AI research, development, and implementation is often difficult. | Sahil et al.[8],Nishant et al. [18] |
| | (A4) Limited digital infrastructure | Inadequate internet connectivity and unreliable power supply hinder the deployment and use of AI technologies. | Fowdur et al. [19] |
| | (A5) Regulatory and policy frameworks | Many developing countries lack robust policies and regulations to govern AI usage and ensure data privacy and security. | Jan et al. [13] |

| | | | |
|---|---|---|---|
| Social (D2) | (A6) Cultural and social barriers | Cultural norms and societal values may resist the adoption and application of AI technologies. | Fowdur et al. [19], Cubric [4] |
| | (A7) Language and localization | Language differences and the need for localization of AI applications can limit their effectiveness and accessibility. | Kent et al. [20], Jan et al. [13] |
| | (A8) Shortage of skilled workforce | A lack of trained professionals and experts in AI and related fields can limit the development and maintenance of AI solutions. | Yadav et al. [5]; Bhutoria [11] |
| | (A9) Digital literacy divide | Significant gaps in digital literacy can prevent the effective use of AI technologies by the general population. | Sharma et al.[10] |
| | (A10) Resistance to change | Fear of job displacement and mistrust of new technologies can lead to resistance from various stakeholders, including employees and traditional industries. | Kulkov et al. [21] |
| | (A11) Low awareness and understanding | Limited awareness and understanding of AI's potential benefits and risks among policymakers, businesses, and the general public. | Al-Sharafi et al. [22], Kulkov et al. [21] |
| Environmental (D3) | (A12) Environmental impact | The energy consumption and carbon footprint associated with AI technologies can be significant, posing environmental concerns. | Farahani and Ghasemi [16], |
| | (A13) Integration with existing systems | Difficulties in integrating AI solutions with existing systems and processes. | Sahil et al. [8] |
| | (A14) Cybersecurity risks | AI systems are vulnerable to cyber-attacks, which can compromise data security and privacy. | Camacho [23],Bhutoria [11] |
| Other (D4) | (A15) Data Scarcity and quality | Insufficient availability of high-quality and relevant local data hampers the training and accuracy of AI models. | Jankovic and Curovic [24],Yadav et al. [5] |
| | (A16) Ethical and bias concerns | AI systems can perpetuate existing biases and raise ethical concerns, particularly in diverse and socio-economically stratified societies. | Zhao and Gómez Fariñas [25] |
| | (A17) Intellectual property issues | Concerns about intellectual property rights and access to AI technologies can hinder collaborative efforts and innovation. | Nishant et al. [26], Javaid et al. [6] |
| | (A18) Practical implementation challenges | Practical difficulties in deploying, scaling, and maintaining AI solutions in resource-constrained settings can limit their impact. | Javaid et al. [6] |

## 3. RESEARCH PROCESS

The proposed decision-making model for AI adoption to achieve SDGs was tested based on an integrated Fuzzy DEMATEL-TOPSIS composed of four phases as shown in Fig. 1, and the details are as follows:

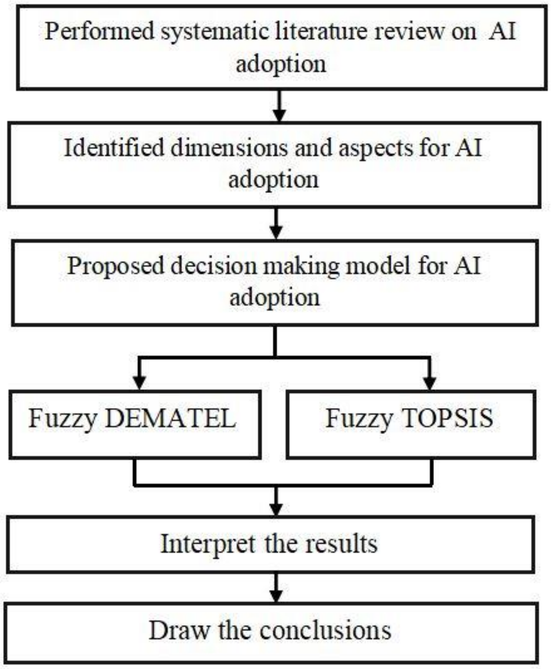
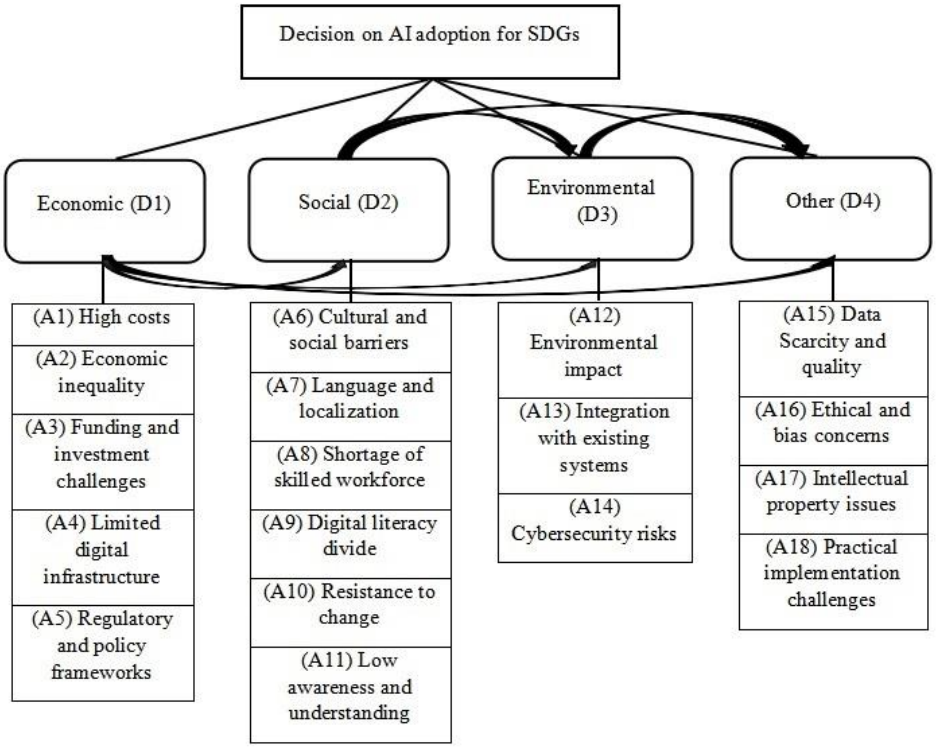



Fig. 1. Research flowchart.

### 3.1 Proposed decision-making model

It is evident from the review of the literature that the majority of the studies on AI adoption were conducted from a single stakeholder point of view [9]. Moreover, it is observed that aspects of social and other AI adoption were not been investigated in the context of developing nations. The reason could be that organizations in developing nations are still at the initial stage of AI adoption. According to Kulkov et al. [21], the effectiveness of enterprises in implementing AI is linked to sustainable development. Therefore, this study's main objective is to close this gap via a decision-making model for AI adoption to achieve SDGs in the context of developing countries. Due to a variety of reasons, AI adoption in developing countries is difficult and also there has to be a smooth transition of technology.

Three levels of the hierarchical model, as shown in Fig. 2. The first level goal is to decide whether to use AI to help achieve the SDGs. Level 2 comprises various dimensions, such as economic, social, environmental, and other. Level 4 includes 14 aspects [16-23]. The main objective of this research is to know which factor in the context of developing countries might significantly affect the adoption of AI. In addition, this study will contribute realistic data for the industry and researchers by identifying the relationship between dimensions and rankings of the aspects.




Note: D means dimension, and A means aspect.

Fig. 2. Proposed decision-making model for AI adoption.

### 3.2 Applied methods

To determine the relative importance of different aspects and relationships that exist between these dimensions in the model, we conducted data analysis in this study using the Fuzzy DEMATEL-TOPSIS methodology. The integration of Fuzzy DEMATEL-TOPSIS provides a robust hybrid model for decision-making in complex environments where criteria are interrelated, and uncertainty is prevalent. Fuzzy DEMATEL is used to classify and map the causal relationships among decision criteria, distinguishing between cause and effect groups, thus offering a structured understanding of how dimensions influence each other. The model addresses the vagueness and ambiguity often present in expert evaluations, enabling a more accurate depiction of the interdependence among dimensions by incorporating Fuzzy logic [27]. Once the causal structure is clarified, Fuzzy TOPSIS is employed to rank the aspects based on their proximity to an ideal solution with both negative and positive ideal solutions being considered to identify the best possible option under uncertainty [28]. This integration provides a two-fold advantage: Fuzzy DEMATEL handles the complexity of interactions, while Fuzzy TOPSIS focuses on prioritizing aspects, ensuring that decision-makers can account for both the influence of aspects and the optimal ranking of solutions. This approach has been effectively applied in various fields, including environmental sustainability [29], technology adoption [30], and supply chain management [31] offering a versatile and comprehensive decision-making tool. The ensuing parts will provide a detailed discussion of the methodology utilized.

3.2.1 Fuzzy DEMATEL steps

In this study, the Fuzzy DEMATEL approach was employed to evaluate the interactions between different dimensions in the decision-making model (Fig. 2). Since the experts' recommendations were derived from their own subjective experiences, the final decision might not have contained numerous misunderstandings or errors. Where uncertainty and ambiguity can be effectively handled with the help of Fuzzy set theory. Moreover, the MCDM technique is necessary to create an extended crisp to the scenarios involved with respect to decision-making in a Fuzzy environment. The DEMATEL technique was utilized to obtain the results by combining seven-point linguistic terms with Triangular Fuzzy Numbers (TFNs), as shown in Table 2. This study uses both the Fuzzy logic with DEMATEL approach to capitalize on the potential of aspects for AI adoption.

**Table 2. The fuzzy scale correspondence.**

| Fuzzy values | Linguistic terms |
|---|---|
| (0,0.05,0.15) | Very low (VL) |
| (0.10,0.20,0.30) | Low (L) |
| (0.20,0.35,0.50) | Medium low (ML) |
| (0.30,0.50,0.70) | Medium (M) |
| (0.50,0.65,0.80) | Medium high (MH) |
| (0.70,0.80,0.90) | High (H) |
| (0.85,0.95,1) | Very high (VH) |

Similar to TFNs, trapezoidal numbers have also been employed with MCDM techniques [32, 33]. The TFNs were effectively utilized in this work to enhance overall assessment. The Fuzzy DEMATEL analysis process was modified and used in this work [9].

Step 1: Creating the impact matrix in Fuzzy linguistic assessment

The linguistic effect assessment matrix was developed based on expert input using a seven-point Fuzzy scale as shown in Table 2. One dimension's impact on the other dimensions was examined using impact matrix. A symbol that shows the dimension ‘i’ influence over dimension ‘j’ is called ‘xij’. It is significant to note that VL (i.e., 0,0.05,0.15) is the value at the diagonal crossing point on the direct inflectional matrix ‘i=j’. The formula Xk = [xkij] can be used by each expert to generate a non-negative n × n matrix. Therefore, the N distinct experts determine the N matrices (X1, X2, etc).

Step 2: Constructing the Fuzzy direct relationship matrix (A)

Fuzzy logic terminology was created to reflect the Fuzziness observed during the assessments [34]. Each linguistic term was written in the following order (Table 2) to describe an undefined event. Fig. 3 depicts a linguistic value between 0 and 1 derived from the realm of discourse [9].

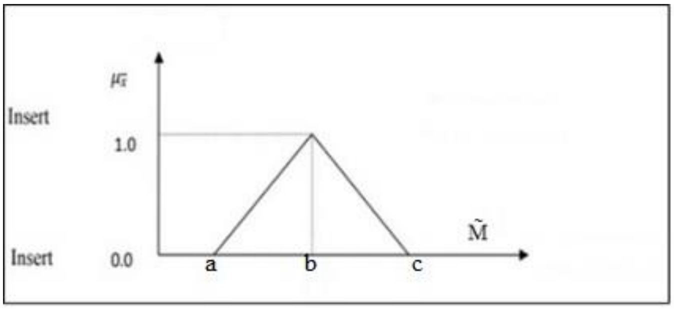



Fig. 3. Visual depiction of the triangle model.

Fig. 3 shows the Fuzzy linguistic scale employed to convert the effect of evaluations into linguistic terms. Furthermore, this study utilized a triangle (a, b, c) to show each Fuzzy linguistic term to simplify the Fuzzy event description and get a better understanding. The presumptive formula is $X_{ij}^{k} = a_{ij}^{k}, b_{ij}^{k}, c_{ij}^{k}$, where $1 \leq k \leq K$, is the $k^{th}$ participate in the research to determine how aspect 'i' effects aspect 'j'. An n × n matrix was formed if 'K' is the number of experts with the potential values of k being 1, 2, 3, 4, etc.... "n" signifies the total number of individuals who participated in the research in Eq. (1).

$$a_{ij} = \frac{1}{k\sum x^{kij}} \tag{1}$$

Subsequently, the Fuzzy numbers were converted into crisp numbers as part of the Defuzzification process, which opened the way for matrix operations. The Defuzzification process for matrix (A) is performed by using Eq. (2).

$$I_T = \frac{1}{6}(a + 4b + c) \tag{2}$$

Step 3: Generate normalized initial direct relationship matrix (D)

$$m = \min\left[\frac{1}{\max\Sigma_{j=1}^{n}|a_{ij}|}, \frac{1}{\max\Sigma_{i=1}^{n}|a_{ij}|}\right] \tag{3}$$

$$Z = m \times A \tag{4}$$

Step 4: Form the total relationship matrix

$$T = Z - (I - Z)^{-1} \tag{5}$$

Here, T: total relationship matrix; I: identity matrix

Step 5: Calculate the sum of rows (R) and sum of columns (C)

$$R= [\ \textstyle\sum_{j=1}^{n} t_{ij}]_{n\ X\ 1} \tag{6}$$

$$C= [\ \textstyle\sum_{i=1}^{n} t_{ij}]_{1\ X\ n} \tag{7}$$

The overall influence of aspect 'i' on aspect 'j' is indicated by the value of 'R'. The entire influence that aspect 'i' had as a result of aspect 'j' is represented by the letter 'C'.

Step 6: Generate the cause-and-effect graph

The datasets (C+R; C-R) were used to generate a graph divided into cause and effect groups. We used the horizontal axis, represented by (C+R), to determine prominence and overall impact in terms of influence and power. The (C+R) axis is a vertical axis that depicts cause/effect classification across dimensions. The (C-R) dimension is then regarded as belonging to the cause category if its value is positive. Similar to this, an aspect is said to have an impact if its value is greater than zero and negative on the C-R axis [30]. Furthermore, the cause-and-effect graph was employed to illustrate primary connections between the dimensions, highlighting their interdependence through the use of arrows.

### 3.2.2 Fuzzy TOPSIS steps

The Fuzzy TOPSIS technique incorporates expert opinions into a framework for making decisions based on a variety of criteria and offering the best solution to a situation with a high degree of ambiguity [35]. Fuzzy TOPSIS technique considers numerous criteria when addressing such decision-making difficulties [35]. In the current research, we applied the Fuzzy TOPSIS method to determine the most important aspects that experts have to consider the intricacies before introducing AI adoption to achieve SDGs. The data was collected based on the Fuzzy scale as shown in Table 2.

The following steps must have to be completed to identify aspects that are most helpful for k responders Dr ($r$ = 1, 2..., k) to solve a decision-making problem with n aspects and m dimensions Ai = (1, 2..., $n$). The following section provides an outline of the steps involved in carrying out the procedure of Fuzzy TOPSIS method. The following Eq. (8) and (9) are used to calculate aspects weights and the dimensions ratings.

$$w_j = \frac{1}{k}\,[w_j^1 + w_j^2 + \cdots + w_j^k] \tag{8}$$

$$x_{ij} = \frac{1}{k}\,[x_{ij}^1 + x_{ij}^r + \cdots + x_j^k] \tag{9}$$

Where the weight of $j$th criterion ($C_j$) is stated by $W_r^j$.
The following Eq. (10) and (11) are used to generate Fuzzy decision matrices for each factor and the alternative (D).

$$W = [w_1 + w_2 + \cdots + w_m] \tag{10}$$

$$D= \begin{array}{c} \\ A_1 \\ A_j \\ A_n \\ \end{array} \begin{bmatrix} X_{11} & X_{12} & X_{1j} & X_{1m} \\ . & . & . & . \\ . & . & . & . \\ X_{n1} & X_{n2} & X_{nj} & X_{nm} \end{bmatrix} \tag{11}$$

Building normalized Fuzzy decision matrix (R) requires applying the following Eq. (12)-(14).

$$R = \left[\mathrm{r}_{\mathrm{ij}}\right]_{\mathrm{m}\times\mathrm{n}} \tag{12}$$

$$\mathrm{r}_{ij} = \left(\frac{l_{\mathrm{ij}}}{u_{\mathrm{ij}}^{+}}, \frac{m_{\mathrm{ij}}}{u_{\mathrm{j}}^{+}}, \frac{u_{\mathrm{ij}}}{u_{\mathrm{j}}^{+}}\right) \text{ and } u_j^{+} = max_i u_{ij} (\text{benefit criteria}) \tag{13}$$

$$\mathrm{r}_{ij} = \left(\frac{l_j^{-}}{u_{\mathrm{ij}}}, \frac{l_j^{-}}{m_{\mathrm{ij}}}, \frac{l_j^{-}}{l_{\mathrm{ij}}}\right) \text{ and } l_j^{-} = max_i l_{ij} (\text{cost criteria}) \tag{14}$$

Using the following Eq. (15) create the weighted normalized decision matrix (V).

$$V = \left[v_{\mathrm{ij}}\right]_{\mathrm{m}\times\mathrm{n},} v_{ij} = \mathrm{X}_{\mathrm{ij}} \times \mathrm{w}_{\mathrm{j}} \tag{15}$$

Using the following Eq. (16) and (17), one can better estimate the Fuzzy Negative Ideal Solution (FNIS) and Fuzzy Positive Ideal Solution (FPIS).

$$A^{-} = \left\{v_1^{-}, v_j^{-}, \ldots, v_m^{-}\right\} \tag{16}$$
$$A^{+} = \left\{v_1^{+}, v_j^{+}, \ldots, v_m^{+}\right\} \tag{17}$$

where $v_j^{+} = (1,1,1)$ and $v_j^{-} = (0,0,0)$.
Using the following Eq. (18)- (20), we determine the distances indicated of each alternative from $v_j^{+}$ and $v_j^{-}$.

$$\mathrm{d}_i^{+} = \sum_{\mathrm{j}=1}^{\mathrm{n}} \mathrm{dv}(v_{ij}, v_j^{+}) \tag{18}$$

$$\mathrm{d}_{\mathrm{i}}^{-} = \sum_{\mathrm{j}=1}^{\mathrm{n}} \mathrm{dv}(v_{ij}, v_j^{-}) \tag{19}$$

$$\mathrm{d}(\mathrm{x},\mathrm{z}) = \sqrt{\frac{1}{3}\left[(l_x - l_z)^2 + (\mathrm{m}_x - \mathrm{m}_z)^2 + (u_x - u_z)^2\right]} \tag{20}$$

Applying the following Eq. (21) to calculate the proximity coefficient $\mathrm{CC}_i$.

$$\mathrm{CC}_i = \frac{\mathrm{d}_{\mathrm{i}}^{-}}{\mathrm{d}_{\mathrm{i}}^{+} + \mathrm{d}_{\mathrm{i}}^{-}} \tag{21}$$

We can determine that which options are appropriate and in which decreasing order is based on $\mathrm{CC}_i$.

## 4. DISCUSSIONS ON RESULTS

### 4.1 Fuzzy DEMATEL results

In the initial phase of research, the survey questionnaire was distributed to the experts who are involved in decision-making at both industry and government organizations as shown in Table 3. The primary objective of this survey was to determine the interactions among identified dimensions of AI adoption followed by identifying the significance of each dimension's influence on expert's opinions while adopting AI for the attainment of SDGs. The experts were asked to respond to questions with the Fuzzy scales shown in Table 2. The majority of them had over ten years of professional experience in the industry, and more than five years of work experience in their current position at their respective firms. In addition, each expert has been involved in decision making process at their organization and they had a degree from prestigious Indian educational institutions.

**Table 3. Experts background information.**

| Methods | Sample size | Characteristics of experts | | | | |
|---|---|---|---|---|---|---|
| | | Work place | | Education Level (majority) | Working experience | |
| | | Industry | Non-industry | | At present position | Career experience |
| Fuzzy DEMATEL | 26 | 11 | 15 | Masters | <5 years | >10 years |
| Fuzzy TOPSIS | 21 | 13 | 8 | Under-graduate | >5 years | >10 years |

Fuzzy DEMATEL analysis was performed as described in the previous section (see Section 3.2.1) and the data was organized into matrices for each expert. At the beginning of the analysis, an overall (average) matrix was computed as shown in Table 4 using Eq. (1-2), followed by the direct relationship matrix determined using Eq. (3-4) as shown in Table 5. T-matrix for all interactions was calculated by evaluating the normalized initial direct matrix with Eq. (5) as shown in Table 6. Finally, we calculated C, R, C+R, and C-R values from T-matrix using Eq. (6-7) as shown in Table 7.

**Table 4. Overall matrix.**

| Dimensions | Economic | Social | Environmental | Other |
|---|---|---|---|---|
| Economic | 0.000 | 0.560 | 0.401 | 0.800 |
| Social | 0.744 | 0.000 | 0.800 | 0.560 |
| Environmental | 0.401 | 0.744 | 0.000 | 0.813 |
| Other | 0.201 | 0.201 | 0.401 | 0.000 |

**Table 5. Direct relationship matrix.**

| Dimensions | Economic | Social | Environmental | Other |
|---|---|---|---|---|
| Economic | 0.000 | 0.258 | 0.185 | 0.368 |
| Social | 0.342 | 0.000 | 0.368 | 0.258 |
| Environmental | 0.185 | 0.342 | 0.000 | 0.374 |
| Other | 0.092 | 0.092 | 0.185 | 0.000 |

**Table 6. T-matrix.**

| Dimensions | Economic | Social | Environmental | Other |
|---|---|---|---|---|
| Economic | 0.470 | 0.717* | 0.719* | 0.995* |
| Social | 0.845* | 0.650 | 0.966* | 1.097* |
| Environmental | 0.688 | 0.837* | 0.634 | 1.081* |
| Other | 0.341 | 0.373 | 0.457 | 0.393 |

Note: * ≥0.704

Based on T values from Table 6, the interactions graph was developed as shown in Fig. 4. To draw interactions among the dimensions in this model, the average value of T-matrix was calculated and considered as a threshold value (0.704). The threshold value acts as a basis for constructing relationships. The model depicts key interactions in T-values (Table 6). Fig. 4 illustrates the social (D2) dimension influence rates on economic (D1), environmental (D3), and other (D4). In addition, the economic (D1) dimension influences rates in the environmental (D3) and other (D4) dimensions. The findings reveal that a significant relationship between social (D2) on economic (D1), and the Fuzzy DEMATEL analysis demonstrates environmental (D3) could not influence the other dimension in the model. Fig. 4 describes the proposed interactions among the four dimensions, i.e., economic (D1), social (D2), environmental (D3), and other (D4), which are the net causes of AI adoption in achieving the SDGs. The C-R result in Table 7 shows that the social (D2), economic (D1), and environmental (D3) dimensions are the cause group, and the other (D4) dimension is the effect group to adopt AI to achieve the SDGs.

**Table 7. The C+R and C-R values.**

| Dimensions | C | R | C+R | C-R |
|---|---|---|---|---|
| Economic | 2.901 | 2.344 | 5.245 | 0.557 |
| Social | 3.558 | 2.577 | 6.135 | **0.981** |
| Environmental | 3.240 | 2.777 | 6.017 | 0.463 |
| Other | 1.565 | 3.566 | 5.131 | -2.001 |

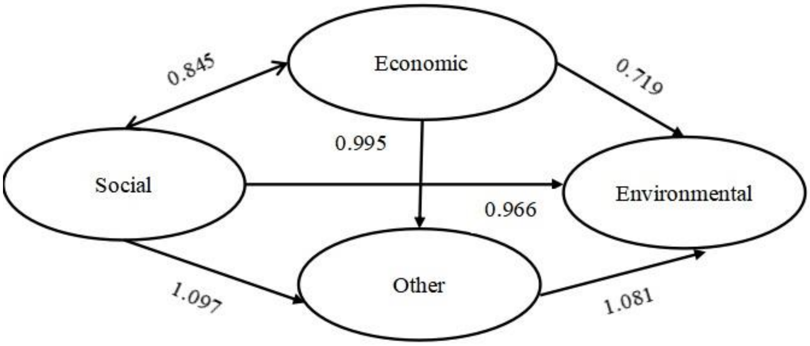



Fig. 4. The four-dimensional interactions graph.

### 4.2 Fuzzy TOPSIS analysis result

In this step, a Fuzzy TOPSIS technique is used to give the ranks to the aspects in the proposed decision-making model. Each aspect's relevance in the decision-making model was assessed by the experts using linguistic scales as shown in Table 2. The average scores corresponding to the average Fuzzy scores of all dimensions are calculated using Eq. (8-21). The final ranking of all these aspects is obtained by the Fuzzy TOPSIS analysis as shown in Table 7. As pertaining to the result obtained, the aspects of digital literacy divide (A9), and shortage of skilled workforce (A8) from the social (D2) dimension are key factors of AI adoption to achieve the SDGs from the experts' perspective. Consequently, these results are crucial for policymakers and government authorities in improving and designing policies towards deploying disruptive technologies and also developing supportive infrastructure to achieve the SDGs. These policies could help improve AI adoption to achieve SDGs in the developing countries, especially the private firms in India.

**Table 7. Overall ranking of aspects in the proposed decision-making model.**

| Aspects | $d_i^-$ | $d_i^+$ | $CC_i$ | Rank |
|---|---|---|---|---|
| A1 | 0.301 | 3.176 | 0.396 | 16 |
| A2 | 0.298 | 3.201 | 0.391 | 17 |
| A3 | 0.489 | 3.189 | 0.642 | 11 |
| A4 | 0.501 | 3.362 | 0.650 | 10 |
| A5 | 0.489 | 3.208 | 0.641 | 12 |
| A6 | 0.624 | 3.344 | 0.811 | 5 |
| A7 | 0.409 | 3.198 | 0.537 | 14 |
| A8 | 0.701 | 3.087 | 0.928 | 2 |
| A9 | 0.749 | 3.064 | 0.993 | 1 |
| A10 | 0.589 | 3.189 | 0.774 | 7 |
| A11 | 0.701 | 3.104 | 0.927 | 3 |
| A12 | 0.654 | 3.201 | 0.858 | 4 |
| A13 | 0.501 | 3.167 | 0.659 | 9 |
| A14 | 0.289 | 3.198 | 0.379 | 18 |
| A15 | 0.312 | 3.421 | 0.403 | 15 |
| A16 | 0.415 | 3.362 | 0.538 | 13 |
| A17 | 0.589 | 3.208 | 0.773 | 8 |
| A18 | 0.601 | 3.344 | 0.781 | 6 |

AI technology intervention as well as its adoption is making news everyday due to its continuous development and been the area of interaction for decision-makers, industry experts, and researchers. These people have observed and identified the progression of AI in various sectors. AI is a trending advanced technology, linking the country's informative intensive ecosystem with its technological advancement and economic growth. Developing countries face a big challenge in implementing AI effectively because of redtapism and difficulties at organizational execution levels. Moreover, the initiation of this policy and its measures is not an easy task or process and needs enhanced analysis. This study's results found that some of the potential aspects have been highlighted and analyzed the interaction among them. These aspects need to be addressed suitably for AI adoption to achieve SDG's. This study aims to identify and analyze the interactions and ranks among the dimensions and aspects of AI adoption to achieve SDGs and to uncover avenues for better decision-making by decision-makers and industry experts.

The current research emphasizes the need to overcome these aspects to gain momentum and promote sustainability within the industry to improve quality of life and achieve expected higher customer satisfaction. From the decision-making model proposed in this study, the aspects digital literacy divide (A9), shortage of skilled workforce (A8), and low awareness and understanding (A11) are the most influential aspects, while the aspect cybersecurity risks (A14) is being the least influential aspect and ranked last among all aspects as shown in Table 7. We find that the aspect shortage of skilled workforce (A8), is line with prior research that demonstrates that it is the most significant aspect in implementation of sustainability supply chain in the context of developing countries [Nishant et al. 18]. However, the results indicate that aspect of digital literacy divide (A9) and low awareness and understanding (A11) are influenced by all aspects and located at the top level as the primary target of the system. These results are in contrast with other studies Yadav et al. [5]; Abdallah [17], they have found that cybersecurity risks (A14) affect the stockholders' trust and Sharma et al. [10] have found that the cultural and social barriers (A6) is also one of the most important aspect for AI adoption.

In developing countries, the digital literacy divides, and the shortage of skilled workforce within the social dimension at present pose significant obstacles to AI adoption for achieving the SDGs. The digital literacy divide in these regions is often pronounced with limited access to digital education and resources, hindering the ability of large segments of the population to engage with AI technologies. This exacerbates social and economic inequalities, as those without digital skills are left behind in an increasingly technology-driven world. In addition, the shortage of a skilled workforce impedes the development and implementation of AI solutions due to insufficient educational infrastructure and opportunities. To overcome these challenges, developing countries need to encourage and focus on targeted investments in education and training and policies fostering digital inclusivity and capacity-building. Bridging these gaps is crucial for harnessing AI's potential to drive sustainable development and uplift marginalized communities.

## 5. RESEARCH IMPLICATIONS

In developing countries, addressing the digital literacy divide and shortage of skilled workforce is crucial for managers aiming to leverage AI for SDGs. Managers must prioritize investments in digital education and training programs to build a digitally literate and skilled workforce. This includes partnering with educational institutions, government bodies, and NGOs to develop a framework that focuses on enhancing and honing digital skills and AI competencies. In addition, managers should also advocate for policies that promote digital inclusion, ensuring that marginalized communities have access to explicit resources and training. Implementing mentorship, apprenticeship programs could also help bridge the skill gap by providing hands-on experience and fostering talent development. Managers with expertise in technology usage may effectively adopt and utilize AI technology to cherish the glory of the SDGs in developing countries by proactively overcoming these difficulties and building a workforce that is more skilled, capable and inclusive. The theoretical implications of this study are multi-fold:

1. The Fuzzy DEMATEL-TOPSIS approach provides robust frameworks for dealing with the complexity and uncertainty inherent in decision-making model. These models help in identifying and analyzing the interactions among various aspects influencing AI adoption, such as economic, social, environmental, and technological aspects.

2. Fuzzy DEMATEL helps in determining the cause-and-effect relationships among dimensions, enabling policymakers and managers to identify key dimensions for AI adoption. Fuzzy TOPSIS aids in ranking and selecting the best alternatives based on their relative closeness to an ideal solution, facilitating informed decision-making.

3. These findings will support the integration of multiple dimensions (economic, social, and environmental) into the decision-making process, aligning with the holistic nature of sustainable development. This multidimensional approach ensures that AI adoption strategies are balanced and consider long-term sustainability goals.

4. By providing a clear framework for evaluating and prioritizing actions, these models help in optimal resource allocation, ensuring that efforts are focused on the most impact areas for AI adoption and sustainable development.

5. The Fuzzy nature of decision-making model allows for flexibility and adaptability in decision-making. They can accommodate changes in the external environment and new information, making them suitable for the dynamic and evolving landscape of AI and sustainable development.

## 6. CONCLUSIONS

This study proposed a decision-making model for AI adoption and tested using the Fuzzy DEMATEL-TOPSIS methodology. However, the findings of Fuzzy DEMATEL analysis were revealed from the experts' points of view. The graph in Fig.4 shows that the social dimension is the net cause. Furthermore, the C-R result in Table 7 shows that the social, economic, and environmental dimensions are the cause group among all dimensions of AI adoption to achieve SDGs. In addition, Fuzzy TOPSIS results revealed the significance of every aspect. The study results revealed that the aspects of digital literacy divide (A9), and shortage of skilled workforce (A8) from the social (D2) dimension are the key aspects for the AI adoption in the developing countries from the expert's perspectives. Therefore, this study can assist business and government bodies to consider AI adoption fully in terms of decision-making. This research study contributions are as follows:

First, the core contribution of this research is a decision-making model that supports AI adoption for SDG's achievement in developing countries. The model incorporates multiple layers of consideration-economic, social, environmental, and other to assist policy-makers and stakeholders in making decisions that are both effective and sustainable. Second, previous studies were conducted from the perspective of developed nations. This study proposed a decision-making model for AI adoption in the context of developing nations. The results of this study, with the insights gained from its practical application should hopefully be useful for enterprises and government authorities in their efforts to promote the acceptance, and adoption of AI. Third, this study's methodology is combined two different MCDM methods with Fuzzy logic, this combined approach enhances decision-making by combining causal analysis and alternative ranking in a Fuzzy environment.

This study has several theoretical and methodological limitations because it examines selective dimensions and their aspects for AI adoption toward achieving the SDGs. Subsequent studies may explore the association of other related dimensions in a similar research setting. Furthermore, this research included the opinions of the organization's experts; future studies would focus on determining the dimensions of AI adoption based on the prevailing conditions in the organization, considering both internal and external factors. In the present study, multiple criterion decision-making approaches have been employed for aspect assessment. Future researchers would apply methods like the Multiple Indicators Multiple Causes Model (MIMIC) or Multilevel Structural Equation Modeling (ML-SEM) to determine the links among aspects and compare their findings with our proposed method. Besides, the present study's AI adoption model was driven by HOT-fit and TOE models. Likewise, future researchers can use organizational theories in the development of robust adaptive models. As a final consideration, to illustrate the robustness of the Fuzzy TOPSIS approach, future researchers are suggested to perform a sensitivity study by adjusting the relative importance of the criterion weights in different settings.

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