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# Prioritising Strategies to Improve Girls' Access to Quality Education: A Hybrid Hyperbolic Fuzzy MCDM Framework with Human and AI Expertise

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**Abstract**

Access to quality education for girls is one of the key targets of the United Nations' Sustainable Development Goals. This study has two major goals. First, this study proposes a hybrid decision framework that integrates hyperbolic fuzzy sets, multi-attitudinal variance, soft cluster rectangle, and integrated simple weighted sum product methods to prioritise strategies that improve access to quality education for girls. Second, this study explores the use of generative AI expertise in a multi-criteria decision-making framework that traditionally uses only human experts. The findings reveal "Effectiveness" to be the most important criterion when assessing the strategies and "Health and Hygiene Interventions" to be the most prioritised strategy. The findings also show a divergence of opinions between the AI experts and human experts in the extremes and alignment of opinions in the non-extremes. The study serves as a foundation for future research on integrating generative AI into decision-making frameworks while also providing policymakers with a structured approach to prioritising strategies for improving girls' education.

**Keywords:** Girls' Education, Soft Cluster Rectangle, Hyperbolic Fuzzy Sets, Generative AI, Hybrid Decision Framework.

# 1 Introduction

Education is recognised as an important determinant of sustainable development, social equity, and economic progress. Despite significant strides made in improving access to quality education for girls, deep-seated gender inequality persists, particularly in regions where societal, economic, and cultural barriers hinder girls' access to quality education. These inequalities are most evident in developing and low-income countries, where poverty, restrictive gender norms, and inadequate infrastructure create significant obstacles for female students. The urgency to bridge this educational gap is highlighted by global initiatives such as the United Nations' "Sustainable Development Goals (SDG)," placing a strong emphasis on achieving gender equality in education. Specifically, SDG 4 aims to ensure inclusive and equitable quality education for all, and SDG 5 aims to empower women and girls [39].
Efforts to improve access to quality education for girls have led to the development of a variety of intervention strategies, each targeting different aspects of the barriers that girls face with respect to educational access. However, understanding, evaluating, and prioritising these strategies remain a critical challenge. The limited resources and time-bound nature of the SDGs necessitate the development of efficient decision-making systems that prioritise the strategies to improve access to quality education for girls. These systems would help the policymakers understand and prioritise strategies based on different contexts. Given the diverse and multidimensional nature of barriers to girls' education, "Multi-Criteria Decision Making (MCDM)" methods emerge as valuable tools for prioritising the strategies to improve educational access for girls. The MCDM methods offer structured approaches to assess, compare, and prioritise educational strategies based on multiple, often conflicting criteria. However, the traditional MCDM approaches face limitations when dealing with uncertainty, imprecise data, and subjective judgements—all of which are inherent in social policy decisions. Human experts such as educators, policymakers, and social workers bring valuable domain-specific knowledge and experience. However, their inputs may be prone to cognitive fatigue, response bias, and individual subjectivity. These may get amplified when using traditional data collection methodology such as the classical Likert scales due to it's rigidity, and to address these, interpreting the data using fuzzy logic has been proposed as a viable solution [8]. Prasad and Pandey [31] discuss the idea of "Wisdom of Generative Artificial Intelligence Crowd" to overcome limitations posed by "Wisdom of Crowd". Similarly, drawing from Licklider's vision of "man-computer symbiosis", Filip [18] discusses how "Artificial Intelligence (AI)" can augment human intellect and enable new styles of work. Building on these insights, this study hypothesizes that AI-based experts, specifically large language models that were trained on extensive datasets, can be employed alongside human experts in MCDM processes. By integrating large language models based evaluations with human judgment, this hybrid approach aims to provide a more robust and scalable framework for prioritising strategies that improve access to quality education for girls.
The research questions this study aims to address are:

- (RQ1) What are the strategies that improve access to quality education for women?
- (RQ2) What is the priority of these strategies when evaluated against various assessment criteria?
- (RQ3) Can generative AI be used as experts in MCDM-based decision frameworks alongside human experts?

In brief, this study has the following components:

- Identification of strategies: Strategies that can improve access to quality education for girls are identified through a comprehensive literature review.
- Data collection: Ratings of strategies on various criteria and the importance of the criteria are collected using a questionnaire from human experts and AI experts. The data is interpreted using "Hyperbolic Fuzzy Set (HYFS)" to effectively model uncertainty [13].
- Weight estimation of experts: Weight values of the experts are estimated using the multi-attitudinal variance method.

- Weight estimation of criterion: Weight values of the criterion are estimated using the "Soft Cluster Rectangle (SCR)" method [45].
- Strategies prioritisation: The ranks of the strategies are computed using the "Integrated Simple Weighted Sum Product Method (WISP)" method [36].

Ultimately, this study aims to support policymakers, educators, and development organisations in prioritising effective, inclusive, and sustainable interventions for promoting girls' education. Thus, the study contributes to the broader goal of achieving educational equity and gender equality on a global scale.

## 2 Literature review

In this section, a literature review of various strategies for improving access to quality education for girls and MCDM methods for education and gender equality was performed.

### 2.1 Studies on strategies to improve access to quality education for girls

In this section, some relevant literature that discusses strategies, policy interventions, and approaches to improve access to quality education for girls has been reviewed. Researchers working in the field of policy and gender have considered various barriers to quality education faced by girls. The strategies have been categorized into six distinct groups, each targeting a specific barrier to girls attaining quality education. The descriptions and studies supporting the strategies are given in Table 1.

### 2.2 Studies on MCDM for access to education and gender equality

Wang et al., [40] studied factors affecting "women's participation in engineering education" using a fuzzy "Decision Making Trial and Evaluation Laboratory (DEMATEL)" [19] approach. Adhikari et al., [1] studied the factors affecting the empowerment of women in India, using an "Analytic Hierarchy Process (AHP)" [34] and "Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS)" [21] approach. Similarly, Yıldırım and Köroğlu, [43] used a fuzzy AHP-TOPSIS approach to evaluate social indicators of women's empowerment. Huang et al., [20] developed a fuzzy TOPSIS framework to evaluate strategies that improve e-teaching adoption in Indian educational organisations. Adhikari et al., [2] evaluated "women's empowerment in different states of India" using an entropy and "Vise Kriterijumska Optimizacija I Kompromisno Resenje (VIKOR)" [44] approach. Ayçin et al., [5] applied MCDM methods such as "Method based on the Removal Effects of Criteria (MEREC)" [22] and "Measurement of Alternatives and Ranking according to COmpromise Solution (MACROS)" [37] approaches to evaluate women's human development level across different countries. From these studies it can be noted that a variety of MCDM approaches have been used in the literature in the context of education and gender. However, usage of MCDM approaches, particularly to evaluate strategies that improve access to education for women remains limited. A notable limitation across these studies is the lack of consideration towards expert weights. Generative AI's potential to provide inputs to MCDM approaches has not been explored in the literature. Table 2 summarises the characteristics of the MCDM approaches used in the discussed studies.

## 3 Methodology

In this section, the methodologies and decision frameworks adapted to evaluate the strategies to improve access to quality education for girls while simultaneously considering multiple criteria and experts have been described.

Table 1: Strategies that improve access to quality education for girls

| Strategy | Description | Source |
|---|---|---|
| Financial Interventions | To target the economic barriers faced by poor families in providing education to their female children, policymakers have developed multitudes of strategies. These strategies address the direct and indirect costs of schooling, as well as the opportunity costs families incur when sending girls to school instead of engaging in household labor or income-generating activities. The strategies that address the economic barriers can be further classified into three subgroups: conditional monetary incentives, unconditional monetary incentives, and subsidies. Conditional monetary incentives involve the students or the families receiving financial payments contingent on specific behaviors such as regular school attendance, and academic performance. | [32], [15], [4], [11], [27], [16] |
| Accessibility and Infrastructure Interventions | Improving physical accessibility and infrastructure targets the physical and safety barriers that prevent girls from attending and staying in school. The strategy focuses on creating physical environments and providing solutions through interventions that ensure the safety, comfort, and accessibility of educational facilities making it easier for girls to participate fully in the learning process. These include: providing transport facilities, bringing schools physically closer to marginalized communities, and improving local facilities | [23], [17], [29], [9], [28], [25] |
| Communal Advocacy and Cultural Interventions | Community advocacy and cultural change targets the societal norms and practices that hinder girls' access to education. Engaging communities through awareness campaigns, local leadership involvement, and grassroots movements can challenge and transform discriminatory attitudes towards girls' education. These include campaigns like "Beti Bachao Beto Padhao" in India, and "Campaign for Female Education" in Ghana. The studies show that while many of these programs may not yield significant results in the short term, they play a crucial role in laying the groundwork for long-term change in girls' education. | [26], [10], [3] |
| Teacher-Oriented Interventions | Teacher-oriented interventions play a crucial role in improving girls' access to education by addressing barriers related to gender representation and pedagogical practices. These strategies involve not only the recruitment and training of teachers but also enhancing the support system for educators to foster an inclusive and supportive learning environment for girls. | [14], [16], [24] |
| Health and Hygiene Interventions | Health and hygiene interventions address the barriers posed by inadequate sanitation facilities, menstrual health management, and poor overall health, which disproportionately affect girls' education. These interventions aim to create a supportive environment where girls can attend school consistently without being hindered by health-related challenges. Studies highlight the role of health and hygiene interventions in improving educational outcomes for girls particularly those in under-served and marginalized communities, where the associated barriers are most pronounced. | [42], [35] |
| Technology-Driven Interventions | Technology-driven interventions aim to leverage digital tools and platforms to address barriers to related to limited infrastructure or teacher availability and focus on reducing gender disparities in access to educational technology. Various studies highlight the impact of e-learning platforms, mobile applications, and digital resources in improving access to education for girls. | [33], [30], [47] |

Table 2: Summary of studies on MCDM for education and gender equality

| Source | Fuzzy used | MCDM approaches used | Pair-wise comparison avoided | Criteria weights considered | Expert weights considered | Generative AI expertise used |
|---|---|---|---|---|---|---|
| [40] | Interval type 2 trapezoidal fuzzy | DEMATEL | ✗ | NA | ✗ | ✗ |
| [1] | None | AHP-TOPSIS | ✗ | ✓ | ✗ | ✗ |
| [43] | Triangular fuzzy | AHP-TOPSIS | ✗ | ✓ | ✗ | ✗ |
| [20] | Triangular fuzzy | TOPSIS | ✓ | ✗ | ✗ | ✗ |
| [2] | Generalized triangular intuitionistic fuzzy | Entropy-VIKOR | ✓ | ✓ | ✗ | ✗ |
| [5] | None | MEREC-MACROS | ✓ | ✓ | ✗ | ✗ |

### 3.1 Preliminaries

HYFS was first introduced by Dutta and Borah [13] to address the limitation faced by traditional fuzzy sets, such as q-rung ortho pair fuzzy sets, by using a product-based constraint rather than a sum-based constraint. The product-based constraint and the operators proposed by Dutta and Borah [13] have been hypothesised to provide more flexible and accurate modelling of uncertainties in real-world scenarios. Researchers have adapted the HYFS for various applications, such as Banik and Dutta [7] have used the HYFS-based framework in determining crime zones in a city. The basic concepts and formulations regarding the HYFS are discussed below.

**Definition 1 [13].** A HYFS $H_X$ for a reference set $X$, is given by

$$H_X = \{x, \mu_h(x), \nu_h(x) \mid \forall x \in X\} \tag{1}$$

$$\mu_h(x), \nu_h(x) \in [0, 1] \tag{2}$$

$$0 \leq \mu_h(x) \cdot \nu_h(x) \leq 1 \tag{3}$$

where, $\mu_h(x)$ and $\nu_h(x)$ are the degrees of membership and non-membership for a given element $x \in R$ to the HYFS $H_X$ respectively.

**Definition 2 [13].** For a HYFS $H_X$, the indeterminateness $\varphi(H_x)$ is given by

$$\varphi(H_x) = 1 - \mu_h(x) \cdot \upsilon_h(x), \forall x \in X \tag{4}$$

**Definition 3 [12],[13].** The basic unary and binary operations for two HYFS $H_X$, and $H_Y$ for the reference sets $X$, and $Y$ are given by:

$$\text{Score: } S(H_X) = 2\mu_h(x) - \mu_h(x) \cdot \nu_h(x),\ \forall x \in X \tag{5}$$

$$\text{Power: } H_X^\gamma = \left(\mu_h(x)^\gamma, 1 - (1 - \nu_h(x))^\gamma\right),\ x \in X,\ \gamma > 0 \tag{6}$$

$$\text{Scalar multiplication: } \gamma \cdot H_X = (1 - (1 - \mu_h(x))^\gamma, \nu_h(x)^\gamma),\ x \in X, \gamma > 0 \tag{7}$$

$$\text{Complement: } H_X^c = (1 - \nu_h(x), 1 - \mu_h(x)),\ x \in X \tag{8}$$

$$\text{Addition: } H_X + H_Y = (\mu_h(x) + \mu_h(y) - \mu_h(x) \cdot \mu_h(y), \nu_h(x) \cdot \nu_h(y)),\ x \in X, y \in Y \tag{9}$$

$$\text{Multiplication: } H_X \times H_Y = (\mu_h(x) \cdot \mu_h(y), \nu_h(x) + \nu_h(y) - \nu_h(x) \cdot \nu_h(y)),\ x \in X, y \in Y \tag{10}$$

the equations (5)-(10) will aid in the development of the methodology.

### 3.2 Estimation of expert weight using multi-attitudinal variance

This section proposes a set of procedures that uses a multi-attitudinal variance method to assign weights to experts. Expert weight estimation is important for any real-world decision problem involving human participants because cognitive fatigue and response bias can impact the inputs given by human participants sampled using convenience sampling. This proposed multi-attitudinal variance method has the following assumptions.

**Hypothesis 1.** Higher variance in expert-given input suggests a broader range of evaluations and usage of the full range of the response scale rather than defaulting to a particular opinion, thus a sign of lower response bias.

**Hypothesis 2.** Lower variance in expert-given input suggests consistency and focused evaluations rather than providing random responses, thus a sign of lower cognitive fatigue.

When considering hypothesis 1 alone, experts with higher variance should be given higher importance. When considering hypothesis 2 alone, experts with lower variance should be given higher importance. In the multi-attitudinal variance method for expert weight estimation, both hypotheses are considered equally.

The steps for the estimation of expert weight using the multi-attitudinal variance method are as follows:

*Step 1:* For each expert $e$, a decision matrix $X^{(e)} = \left[x_{ij}^{(e)}\right]_{m \times n}$ is to be constructed, such that

$x_{ij}^{(e)}$ is the value given by that particular expert for the $i^{\text{th}}$ alternative on the $j^{\text{th}}$ criterion. Where $i = 1, 2, 3, \ldots, m$, $j = 1, 2, 3, \ldots, n$, and $e = 1, 2, 3, \ldots, k$.
*Step 2:* The decision matrix $X^{(e)}$ is flattened to a 1-dimensional vector of size $1 \times m \cdot n$.
*Step 3:* The variance value of the flattened decision vector $X^{(e)}$ is computed.

$$\text{var}^{(e)} = \frac{1}{m \cdot n} \sum_{ij=1}^{m \cdot n} \left( x_{ij}^{(e)} - \bar{x}^{(e)} \right)^2 \tag{11}$$

where, $\text{var}^{(e)}$ is the variance $x_{ij}^{(e)}$ is a value from the flattened decision vector $X^{(e)}$, and $\bar{x}^{(e)} = \frac{1}{m \cdot n} \sum_{ij=1}^{m \cdot n} x_{ij}^{(e)}$ is the mean of the flattened decision vector $X^{(e)}$.
*Step 4:* The variance values are aggregated into the vector $V = \left[\text{var}^{(e)}\right]_{1 \times k}$.
*Step 5:* The variance vector $V$ is normalised $W = \left[we^{(e)}\right]_{1 \times k}$ using equation (12).

$$we^{(e)} = \frac{\text{var}^{(e)}}{\sum_e \text{var}^{(e)}} \tag{12}$$

The normalised variances $we^{(e)}$ capture hypothesis 1.
*Step 6:* To capture hypothesis 2, the inverse of $W$, denoted as $W^{-1} = \left[iwe^{(e)}\right]_{1 \times k}$, is calculated as:

$$iwe^{(e)} = \frac{1 - we^{(e)}}{\sum_e (1 - we^{(e)})} \tag{13}$$

*Step 7:* The hypothesis 1 values $we^{(e)}$ and hypothesis 2 values $iwe^{(e)}$ are aggregated to estimate the final expert weight.

$$wk^{(e)} = \alpha \cdot we^{(e)} + (1 - \alpha) \cdot iwe^{(e)} \tag{14}$$

where $wk^{(e)}$ is the estimated expert weight that considers both hypotheses and $\alpha$ is a parameter set to 0.5.

### 3.3 Estimation of criteria weights using the soft cluster-rectangle method

In this section, an SCR method for weighting criteria is presented. Criterion weighting is an important procedure in any real-world decision problem. As humans often think in terms of the relative importance of entities, assigning weights to these helps capture the preferences and priorities of the decision-makers. The SCR method proposed by Zakeri et al., [45] is a very efficient criterion weighting method as it avoids using pairwise comparisons used by most traditional methods like DEMATEL and AHP. In this method, the decision-makers assign membership values of each criterion to three clusters: "Vital", "Mediocre", and "Immaterial". These cluster membership values are then used to calculate the weights for the criterion. The steps adapted from the SCR method for this study are as follows:
*Step 1:* For each expert $e$, a decision matrix $X^{(e)} = \left[x_{ij}^{(e)}\right]_{3 \times n}$ is to be constructed, where $x_{ij}^{(e)}$ represents the membership value given by that particular expert for the $j^{\text{th}}$ criterion in the $i^{\text{th}}$ cluster. The clusters are defined as: $\alpha$ is the "Vital" cluster, $\beta$ is the "Mediocre" cluster, $\gamma$ is the "Immaterial" cluster. The membership values satisfy the condition $L \leq x_{ij}^{(e)} \leq H$, where $H = 0.9$ represents the highest possible membership, $L = 0.1$ is the lowest possible membership, and $M = 0.5$ represents a neutral membership.
*Step 2:* The decision matrices $X^{(e)}$ are aggregated to form $X = [x_{ij}]_{3 \times n}$ using the "simple geometric weighted mean," with expert weights $w^{(e)}$ obtained in the previous section:

$$x_{ij} = \prod_e \left( x_{ij}^{(e)} \right)^{wk^{(e)}} \tag{15}$$

*Step 3:* The aggregated decision matrix $X = [x_{ij}]_{3 \times n}$ is converted to a fuzzy representation matrix $\mathcal{N} = [\mu_{ij}]_{3 \times n}$. The $\mu_{ij}$ is a fuzzy representation of $x_{ij}$ in the form of $(l_{ij}, \tau_{ij}, u_{ij})$, where $l_{ij}$ is the lower boundary, $\tau_{ij}$ is the centre, and $u_{ij}$ is the upper boundary of the membership. The conversion of $x_{ij}$ to $\mu_{ij}$ is performed using the following conditions:

$$\text{If } x_{ij} \in [M, H] \text{ and } x_{ij} \geq \frac{M+H}{2}, \quad \mu_{ij} = \left(x_{ij}, x_{ij}, \frac{H + x_{ij}}{2}\right) \tag{16}$$

$$\text{If } x_{ij} = H, \quad \mu_{ij} = \left(\frac{3H+M}{4}, H, H\right) \tag{17}$$

$$\text{If } x_{ij} = M, \quad \mu_{ij} = \left((M-L) - \frac{M^3}{3H}, M, \frac{3HL + M^2}{M}\right) \tag{18}$$

$$\text{If } x_{ij} = L, \quad \mu_{ij} = (L, L, L) \tag{19}$$

$$\text{If } x_{ij} < M, \quad \mu_{ij} = \left(\frac{x_{ij}(x_{ij} + L + 2M)}{2}, x_{ij}, x_{ij}\right) \tag{20}$$

$$\text{If } x_{ij} > M \text{ and } x_{ij} < \frac{M+H}{2}, \quad \mu_{ij} = \left(\frac{3x_{ij} + M}{4}, x_{ij}, x_{ij}\right) \tag{21}$$

*Step 4:* The weights $\omega_\alpha, \omega_\beta, \omega_\gamma$ for each cluster are to be set in such a way that the weights reflect the importance of members of the clusters. If a cluster is assigned higher weights, then it would mean that the members of the cluster are of higher importance. It is also to be noted that $0 \leq \omega_i \leq 1$, and $\sum_i \omega_i = 1$.
*Step 5:* The cumulative soft cluster rectangle area $\varepsilon_j$ for each criterion $j$ is calculated using the following equation:

$$\begin{aligned}\varepsilon_j = 2\Big(&\omega_\alpha^2 l_{\alpha j}\tau_{\alpha j} + \omega_\alpha^2 l_{\alpha j}u_{\alpha j} + \omega_\alpha^2 \tau_{\alpha j}u_{\alpha j} + \\ &\omega_\beta^2 l_{\beta j}\tau_{\beta j} + \omega_\beta^2 l_{\beta j}u_{\beta j} + \omega_\beta^2 \tau_{\beta j}u_{\beta j} + \\ &\omega_\gamma^2 l_{\gamma j}\tau_{\gamma j} + \omega_\gamma^2 l_{\gamma j}u_{\gamma j} + \omega_\gamma^2 \tau_{\gamma j}u_{\gamma j}\Big)\end{aligned} \tag{22}$$

*Step 6:* The cumulative soft cluster rectangle areas $\varepsilon_j$ are normalized to determine the weight of each criterion $j$:

$$wc_j = \frac{\varepsilon_j}{\sum_j \varepsilon_j} \tag{23}$$

where $wc_j$ represents the weight of criterion $j$.

### 3.4 Estimation of ranks for the strategies using the integrated simple weighted sum product method.

In the section, the WISP method for ranking alternatives is presented. Ranking of alternatives, particularly in real-world decision problems, requires consideration of various criteria, the importance of those criteria, and multiple ways of interpreting how the criteria are combined. The WISP method proposed by Stanujkic et al., [36] is an MCDM ranking method that integrates four different weighted sum and weighted product-based models. The WISP approach has also been adapted for various real-world case studies, such as the study by Ulutaş et al., [38] which used WISP for a sustainable supplier selection problem. The steps adapted from the WISP method for this study are as follows:
*Step 1:* For each expert $e$, a decision matrix $A^{(e)} = \left[a_{ij}^{(e)}\right]_{m \times n}$ is to be constructed, where $a_{ij}^{(e)}$ represents the value given by the particular expert $e$ for the $i^{\text{th}}$ alternative on the $j^{\text{th}}$ criterion. Here, $i = 1, 2, 3, \ldots, m$, $j = 1, 2, 3, \ldots, n$, and $e = 1, 2, 3, \ldots, k$. It should be noted that each criterion $j$ can belong to either a "benefit" or "cost" type.
*Step 2:* The decision matrices $A^{(e)} = \left[a_{ij}^{(e)}\right]_{m \times n}$ are to be normalised to $X^{(e)} = \left[x_{ij}^{(e)}\right]_{m \times n}$ using the following equation:

$$x_{ij}^{(e)} = \frac{a_{ij}^{(e)}}{\max_i a_{ij}^{(e)}} \tag{24}$$

*Step 3:* Four different models adapted from WISP are computed for each $i^{\text{th}}$ alternative from each expert $e$:

$$wsd_i^{(e)} = \left( \sum_{j \in \text{benefit}} x_{ij}^{(e)} \cdot wc_j \right) - \left( \sum_{j \in \text{cost}} x_{ij}^{(e)} \cdot wc_j \right) \tag{25}$$

$$wpd_i^{(e)} = \left( \prod_{j \in \text{benefit}} \left( x_{ij}^{(e)} \right)^{wc_j} \right) - \left( \prod_{j \in \text{cost}} \left( x_{ij}^{(e)} \right)^{wc_j} \right) \tag{26}$$

$$wsr_i^{(e)} = \frac{\sum_{j \in \text{benefit}} x_{ij}^{(e)} \cdot wc_j}{\sum_{j \in \text{cost}} x_{ij}^{(e)} \cdot wc_j} \tag{27}$$

$$wpr_i^{(e)} = \frac{\prod_{j \in \text{benefit}} \left( x_{ij}^{(e)} \right)^{wc_j}}{\prod_{j \in \text{cost}} \left( x_{ij}^{(e)} \right)^{wc_j}} \tag{28}$$

*Step 4:* The values from the four models are to be normalized using the normalization equations (29)-(32) that were adapted from Zavadskas et al., [46].

$$\overline{wsd}_i^{(e)} = \frac{1 + wsd_i^{(e)}}{1 + \max_i \left( wsd^{(e)} \right)} \tag{29}$$

$$\overline{wpd}_i^{(e)} = \frac{1 + wpd_i^{(e)}}{1 + \max_i \left( wpd^{(e)} \right)} \tag{30}$$

$$\overline{wsr}_i^{(e)} = \frac{1 + wsr_i^{(e)}}{1 + \max_i \left( wsr^{(e)} \right)} \tag{31}$$

$$\overline{wpr}_i^{(e)} = \frac{1 + wpr_i^{(e)}}{1 + \max_i \left( wpr^{(e)} \right)} \tag{32}$$

*Step 5:* The overall weights of the alternative $i$ given by expert $e$ is to be computed by finding the mean of the four normalized model values:

$$ws_i^{(e)} = \frac{1}{4} \left( \overline{wsd}_i^{(e)} + \overline{wpd}_i^{(e)} + \overline{wsr}_i^{(e)} + \overline{wpr}_i^{(e)} \right) \tag{33}$$

where $ws_i^{(e)}$ is the weight of the alternative $i$ given by expert $e$, these are to be used to assign ranks with respect to the expert $e$ such that the alternative $i$ with the highest $ws_i^{(e)}$ is given rank 1, and the one with the lowest $ws_i^{(e)}$ is given rank $m$.
*Step 6.1:* Applying steps 1-5 for decision matrices of each expert $e$, $k$ vectors of dimensions $1 \times m$ are obtained. The final rankings are obtained using a rank fusion procedure that takes into consideration the expert weights.
*Step 6.2:* Let the outputs of applying steps 1-5 for each expert $e$ be aggregated into a single matrix $R = \left[ r_i^{(e)} \right]_{k \times m}$, where the $r_i^{(e)}$ represents the rank assigned to the the alternative $i$ using the decision matrix of expert $e$.
*Step 6.3:* Aggregated rank values for each alternative $i$ are obtained using equation (34).

$$ar_i = \sum_{e=1}^{k} r_i^{(e)} * wk^{(e)} \tag{34}$$

where $ar_i$ is the aggregated rank value for each alternative $i$.
*Step 6.4:* The vector $AR = [ar_i]_{i \times 1}$ is then inverted using equation (35).

$$iar_i = \max(AR) - ar_i \tag{35}$$

By performing equation (35), the value of $iar_i$ whose $ar_i$ is the maximum, becomes zero. These $iar_i$ values of the alternatives are then used to find the final rankings of the alternatives.

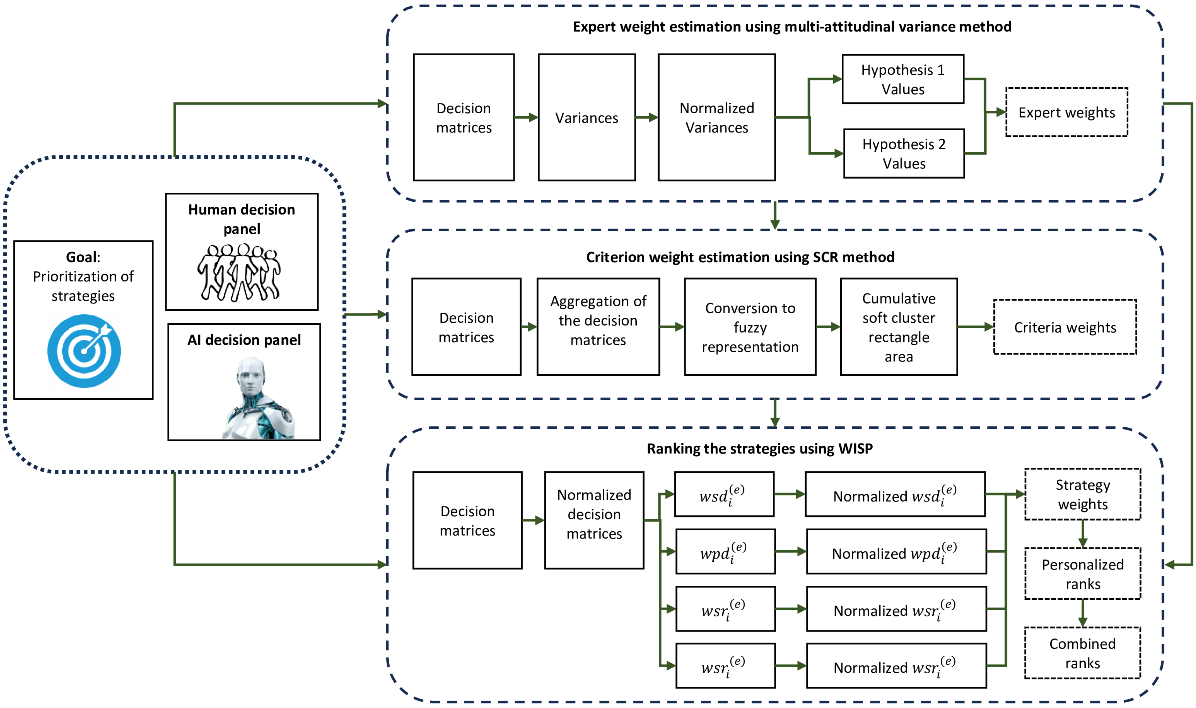


Figure 1: Workflow of the proposed decision framework

### 3.5 Workings of the proposed decision framework

The proposed decision-making framework's simplified workflow has been shown in Figure 1 to help better understand the decision framework. The application of the framework to a real-world case is tackled in the next section. In the decision framework workflow, a panel of $k$ experts who are usually people with a high level of exposure to the respective decision problem is formed. The $k$ experts give their opinion on $m$ strategies versus $n$ criteria and membership of $n$ criteria to the three clusters mentioned in section 3.3. The multi-attitudinal variance method takes in the strategy versus criterion information and gives a $1 \times k$ vector of the expert weights. The SCR method takes in the criterion cluster membership information and gives a $1 \times n$ vector of criterion weights. The WISP method is applied individually on strategy versus criterion information given by each expert to obtain $1 \times m$ vector of personalised ranks; these are then fused using the fusion procedure mentioned in section 3.4 to obtain the combined ranks of the strategies.

## 4 Case study

In this section, the case study of prioritising strategies that improve access to education for girls is presented. The case study considers six strategies: Financial Interventions (S1), Accessibility and Infrastructure Interventions (S2), Communal Advocacy and Cultural Interventions (S3), Teacher-Oriented Interventions (S4), Health and Hygiene Interventions (S5), and Technology-Driven Interventions (S6). These strategies are to be prioritized using the following five criteria: Effectiveness (C1), Long-term Sustainability (C2), Cultural Compatibility (C3), Implementation Complexity (C4), and Implementation Cost (C5). For brevity, the six strategies are hereon referred to as S1, S2, . . ., S6, and the five criteria are referred to as C1, C2, . . ., C5. The criteria C4 and C5 are of the cost type, while the rest are of the benefit type.

Table 3: Demographic summary of the first panel

| Demographic Variables | Subgroups | Number of Experts |
|---|---|---|
| Age | 20 - 40 | 1 |
| | 40 - 50 | 5 |
| | $\geq 50$ | 2 |
| Highest Education | Doctorate | 8 |
| Gender | Male | 4 |
| | Female | 4 |

### 4.1 Data

Two decision panels are constructed to evaluate the strategies and the criterion for the case study. The first panel formed through convenience sampling consists of eight human experts with scholarly backgrounds and substantial work experience in academia and research. These experts were selected because of their background that equips them with advanced skills in evidence-based decision-making. For brevity, the members of the first panel will hereon be referred to as E1, E2, ..., E8. The second panel consists of four state-of-the-art models as of the year 2025, "Chain of Thought" [41] enabled large language models: GPT-4o by OpenAI (A1), Gemini 2.0 Flash by Google (A2), DeepThink R1 by DeepSeek (A3), and Grok 3 by xAI (A4). These models were considered for this study due to their advanced reasoning capabilities, which allow them to simulate structured, step-by-step decision-making processes akin to human experts. For brevity, the members of the second panel will hereon be referred to as A1, A2, ..., A4. A demographic summary of the panel members in the first panel is provided in Table 3.

A custom five-element scale questionnaire to collect the panel members' rating on the criterion and the strategies was designed. The linguistic terms used in the scale for collecting ratings were: Very High, High, Moderate, Low, and Very Low. The questionnaire was provided to the first panel through Google forms. The Table 1 was first given as a prompt to the second panel through their respective websites to set the context, and then the questionnaire in the form of plain text was prompted to the second panel.

### 4.2 Application of the proposed decision framework

The proposed decision framework involves computing the relative importance of experts, estimating criterion weights, and finally assessing the strategies that improve access to quality education for girls. It is to be noted that the framework is applied to the data from each panel independently of each other. The steps that are used to apply the decision framework on the case example on panel member-given data are as follows:

*Step a:* Decision matrices of dimension $6 \times 5$ are formed to store strategies versus criterion data mentioned in section 3.4, and decision matrices of dimension $3 \times 5$ are formed to store criterion versus cluster membership data mentioned in section 3.3. The custom five-element scale data is interpreted using HYFS and is converted to score values using equation (5). Since, in section 3.3 the $H = 0.9$ and $L = 0.1$, the scores are to be normalised to the range of $[0.1, 0.9]$ using min-max normalisation described in equation (36). It is also to be noted that the HYFS values are designed so that the highest membership is 0.9 and the lowest is 0.1, with non-membership being their complement, while the intermediate values are placed equidistantly to ensure a balanced and symmetric transition. The linguistic terms, HYFS values, the respective scores, and normalised scores are described in Table 4.

$$x' = 0.1 + \frac{(x - x_{\min})}{(x_{\max} - x_{\min})} \times (0.9 - 0.1) \tag{36}$$

where $x'$ represents the normalised score, $x_{\min}$ represents the minimum computed score, and $x_{\max}$ represents the maximum computed score.

*Step b:* The procedures mentioned in section 3.2 are applied for each expert given strategies versus criterion data in order to compute the expert weights. Table 5 shows the hypothesis 1 and hypothesis 2 values alongside the computed expert weights for the first decision panel, whereas Table 6 shows the

Table 4: Linguistic terms and conversions

| Linguistic Terms | HYFS | Score | Normalized Score |
|---|---|---|---|
| Very High | (0.9, 0.1) | 1.710 | 0.900 |
| High | (0.7, 0.3) | 1.190 | 0.640 |
| Moderate | (0.5, 0.5) | 0.750 | 0.420 |
| Low | (0.3, 0.7) | 0.390 | 0.240 |
| Very Low | (0.1, 0.9) | 0.110 | 0.100 |

Table 5: Expert weights for the first decision panel

| Expert | Variance | Hypothesis 1 Values | Hypothesis 2 Values | Expert Weights |
|---|---|---|---|---|
| E1 | 0.023 | 0.089 | 0.13 | 0.109 |
| E2 | 0.061 | 0.232 | 0.11 | 0.171 |
| E3 | 0.034 | 0.129 | 0.124 | 0.127 |
| E4 | 0.024 | 0.09 | 0.13 | 0.11 |
| E5 | 0.052 | 0.197 | 0.115 | 0.156 |
| E6 | 0.029 | 0.111 | 0.127 | 0.119 |
| E7 | 0.023 | 0.089 | 0.13 | 0.109 |
| E8 | 0.017 | 0.064 | 0.134 | 0.099 |

same for the second decision panel.

*Step c:* The procedure mentioned in section 3.3 is applied for each expert given criterion versus cluster membership data to compute the criterion weights. It is to be noted that the weights $\omega_\alpha, \omega_\beta, \omega_\gamma$ are set to 0.6, 0.3, and 0.1, respectively. Table 7 shows the criterion weights computed using the data from the first decision panel and the second decision panel independently of each other.

*Step d:* Using the criteria weights obtained from the previous step from the each decision panel and the procedure mentioned in section 3.4 the personalized ranks and the combined ranks for each decision panel is obtained. To obtain the final ranking, the combined ranks from the first decision panel and the combined ranks from the second decision panel are fused together using steps 6.1 to 6.4 from section 3.4, with both panels getting equal weights. The personalised and the combined ranks are described in Table 8. The heat map of the cosine similarity score as defined by equation (37) for the strategies ranks is shown in Figure 2.

$$\text{cosine similarity} = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2} \times \sqrt{\sum_{i=1}^{n} B_i^2}} \tag{37}$$

where $A$ and $B$ are two $n$-dimensional vectors.

# 5 Discussion and conclusion

Education is an important driver of economic growth, and facilitating access to education positively influences the prospects of future generations, especially in developing countries [6]. Improving access to quality education for girls is one of the crucial targets of the United Nations' SDG 4 and 5. To achieve this, a variety of strategies have been proposed by various researchers and policymakers. However, due to the resource and time constraints, it is essential to prioritise the implementation of the strategies in accordance with the implementation context. Various MCDM methods have been designed by researchers; however, they also have various limitations. The MCDM methods that rely on human expert-given opinions are susceptible to the subjectivity of the human experts.

Table 6: Expert weights for the second decision panel

| Expert | Variance | Hypothesis 1 Values | Hypothesis 2 Values | Expert Weights |
|---|---|---|---|---|
| A1 | 0.036 | 0.308 | 0.231 | 0.269 |
| A2 | 0.044 | 0.382 | 0.206 | 0.294 |
| A3 | 0.024 | 0.205 | 0.265 | 0.235 |
| A4 | 0.012 | 0.106 | 0.298 | 0.202 |

Table 7: Criteria weights using both the decision panels

| Criteria | Criterion Weights by AI Experts | Criteria Weights by Human Experts |
|---|---|---|
| Effectiveness (C1) | 0.2957 | 0.2756 |
| Long-term Sustainability (C2) | 0.2957 | 0.1875 |
| Cultural Compatibility (C3), | 0.2552 | 0.2155 |
| Implementation Complexity (C4) | 0.0748 | 0.1694 |
| Implementation Cost (C5) | 0.0785 | 0.152 |

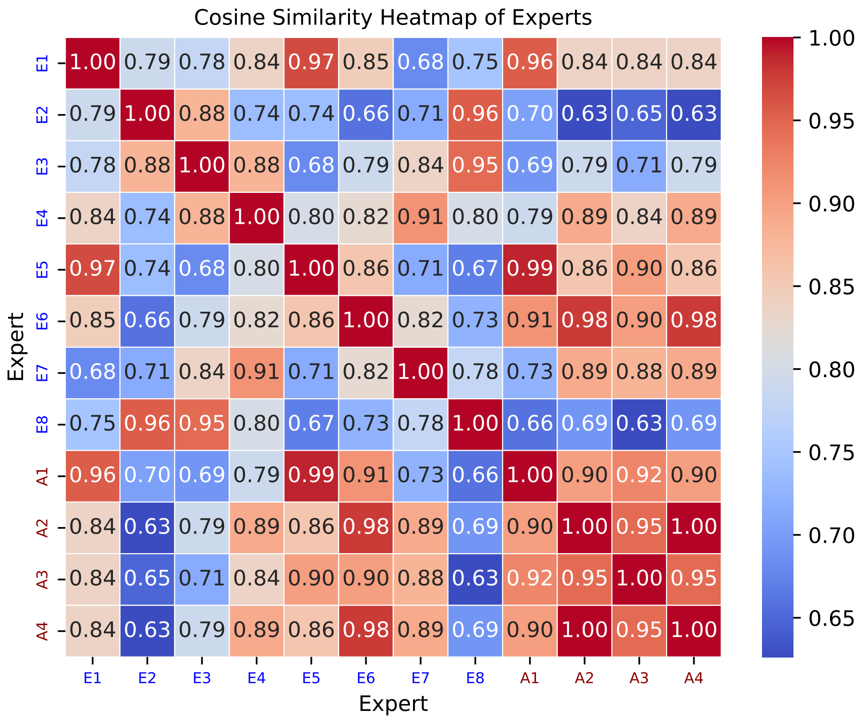


Figure 2: Heat-map of rank cosine similarity between experts

Table 8: The personalized and combined ranks for the strategies

| Expert | Financial Interventions (S1) | Accessibility and Infrastructure Interventions (S2) | Communal Advocacy and Cultural Interventions (S3) | Teacher-Oriented Interventions (S4) | Health and Hygiene Interventions (S5) | Technology-Driven Interventions (S6) |
|---|---|---|---|---|---|---|
| E1 | 3 | 2 | 1 | 5 | 4 | 6 |
| E2 | 2 | 3 | 4 | 6 | 5 | 1 |
| E3 | 2 | 4 | 5 | 6 | 1 | 3 |
| E4 | 1 | 5 | 4 | 3 | 2 | 6 |
| E5 | 4 | 2 | 1 | 3 | 5 | 6 |
| E6 | 6 | 4 | 2 | 3 | 1 | 5 |
| E7 | 3 | 5 | 6 | 1 | 2 | 4 |
| E8 | 2 | 5 | 4 | 6 | 3 | 1 |
| A1 | 5 | 2 | 1 | 3 | 4 | 6 |
| A2 | 5 | 4 | 3 | 2 | 1 | 6 |
| A3 | 5 | 2 | 4 | 1 | 3 | 6 |
| A4 | 5 | 4 | 3 | 2 | 1 | 6 |
| Combined Human | 1 | 4 | 3 | 6 | 2 | 5 |
| Combined AI | 5 | 4 | 3 | 1 | 2 | 6 |
| Combined Final | 2 | 5 | 2 | 4 | 1 | 6 |

In this study, six strategies that improve access to quality education were selected through a comprehensive literature review. Expert ratings on these strategies and criterion to rate these strategies were collected. The collected data was modelled using HYFS to capture uncertainty and overcome limitations of modelling data using traditional fuzzy sets. To mitigate subjectivity caused by response bias and cognitive fatigue, a multi-attitudinal variance method is used to assign weights to the experts. The SCR method is used to estimate criterion weights. Since the SCR method requires cluster membership data, rather than pairwise comparison data, it reduces the size of the questionnaire that the experts would have to give their ratings on, thus causing less cognitive fatigue. The WISP method was then used to rank the strategies. The personalised ranks were obtained for each expert, which was then combined using a fusion procedure. A highlight of this study was that the study explored the idea of using generative AI as an expert for MCDM, taking inspiration from the concept of Wisdom of Generative Artificial Intelligence Crowd" from Prasad and Pandey [31].
The results show that the Health and Hygiene Interventions (S5) were the most prioritised strategy for improving access to quality education for girls alongside Financial Interventions (S1), and Communal Advocacy and Cultural Interventions (S3), whereas Technology-Driven Interventions (S6) was the least prioritised strategy. The combined ranks of the AI and the combined ranks of the human experts showed that both the AI and humans disagreed on which strategy should be the most prioritised and which one should be the least prioritised. However, there was agreement on the relative ranking of the strategies in the middle, suggesting that while AI and human judgement diverged at the extremes, they aligned in assessing the importance of moderately ranked strategies. This result indicates that AI and human decision-making processes may emphasise different factors when identifying the most and least critical strategies; however, they might converge on those that are deemed to be of intermediate priority. The heat map of rank cosine similarity between experts showed that the human experts had relatively high similarity among themselves, with values mostly above 0.70, whereas the AI experts had even higher internal agreement with cosine similarities exceeding 0.90 among themselves. Notably, the similarity between human and AI experts was generally lower, especially for some pairs where the values dropped below 0.70. This reinforces the finding that AI and human experts differed in their prioritisation, particularly at the extremes.
The results of criterion weights showed that both the "cost" type criterion Implementation Complexity (C4), and Implementation Cost (C5) were weighted relatively lower by both the human and AI decision panel. The "benefit" type criterion, Effectiveness (C1) had gotten the highest weighting by both the human and AI decision panel. The weights given to the "cost" type criterion Implementation Complexity (C4), and Implementation Cost (C5) by the AI decision panel were significantly lower (less than 0.08) than the weights given by them to the "benefit" type criterion (more than 0.2). This discrepancy highlights that both humans and AI placed greater emphasis on the perceived benefits of a strategy than on the associated costs. However, AI appears to emphasise benefits even more strongly, potentially underweighting practical constraints such as cost and complexity. This could have implications for decision-making, as AI might favour strategies with high theoretical impact while downplaying feasibility concerns.
In conclusion, this study prioritises the strategies that improve access to education for girls, a key target of SDG 4 and 5, through a decision framework that combines multi-attitudinal variance, SCR, and WISP. The findings reveal Effectiveness (C1) to be the most important criterion when assessing the strategies and Health and Hygiene Interventions (S5) to be the most prioritised strategy to improve access to quality education for girls. The usage of a decision panel consisting of generative AI LLMs for MCDM, the study reveals that AI diverges in the extremes when compared to humans while aligning in the middle. The study contributes to the existing body of literature by:

- Developing a decision-making framework using HYFS, multi-attitudinal variance, SCR, and WISP for prioritisation of strategies that improve access to quality education for girls.

- Proposing the idea that generative AI LLMs have the potential to be used alongside human experts in the context of MCDM.

- Suggesting the strategies that need to be prioritised, alongside the relative importance of criteria to assess those strategies.

The implications of the study are:

- By identifying and prioritising the strategies and the criteria to assess these strategies that improve access to quality education for girls, the study provides policymakers and stakeholders with a robust, data-driven framework for informed resource allocation and strategic planning.
- The integration of generative AI LLMs as experts for MCDM introduces an innovative approach that complements traditional human judgment, potentially enhancing the speed, consistency, and depth of MCDM problems that involve purely human experts.
- The observed divergence between human and AI rankings especially at the extremes, highlight that careful considerations should be made before integrating generative AI into any decision problem. This divergence could also potentially provide complementary perspective to decision problems by offering alternative prioritisation that challenges conventional human biases. While human experts bring contextual understanding and lived experiences, AI can introduce a data-driven, pattern-based approach that may uncover overlooked insights.
- The combined HYFS, multi-attitudinal variance, SCR, and WISP framework developed can also be used in various other contexts beyond education policy, such as healthcare, environmental sustainability, and infrastructure development, where prioritisation of strategies under uncertainty is crucial.

The study, despite the various merits, also has some limitations:

- The framework developed is incapable of interpreting incomplete information
- Since this study represents the first time generative AI has been integrated into MCDM, the findings require further validation through replication across diverse decision-making scenarios to establish the robustness and reliability of AI-driven insights for MCDM.
- The study does not account for dynamic quantitative data that captures the external conditions, such as policy shifts, economic fluctuations, or technological advancements, which could alter the relative importance of the identified strategies over time.

The future studies could explore the possibility of using the developed framework across various other domains to validate its generalisation. The usage of advanced imputation techniques and probabilistic reasoning models to address the limitation of incomplete information should be explored in the future studies. Future studies could also develop various other MCDM frameworks that integrate generative AI for decision-making and leverage adaptive weighting mechanisms to improve decision-making outcomes. The future studies could also examine the ethical and fairness implications of generative AI participation in MCDM to ensure that AI-generated recommendations do not introduce or reinforce biases in decision-making. By addressing the mentioned research directions, the future studies can contribute to the theoretical and practical development of decision-making frameworks that go beyond human expertise.

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## Declarations

The authors have no relevant financial or non-financial interests to disclose.

### Statement of generative AI use

During the preparation of this work, the author(s) used QuillBot to edit and refine the manuscript. The author(s) also used GPT-4o by OpenAI, Gemini 2.0 Flash by Google, DeepThink R1 by DeepSeek, and Grok 3 by xAI to collect data as inputs for the MCDM framework as mentioned in the manuscript. After using these tools/services, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

### Data availability

The anonymized raw input data collected from both human experts and generative AI is available at https://github.com/regiusherder/Strategies-for-Education

### Author contributions

A. Yadav: Conceptualization, Data curation, Method, Software, Writing—original draft; R. Krishankumar: Conceptualization, Method, Prototype, Investigation, Writing—original draft; KS. Ravichandran: Data curation, Method, Investigation, Writing—original draft; V. Zemlickienė: Method, Supervision, Investigation, Writing—Original Draft, Review; Z. Turskis: Method, Supervision, Investigation, Writing—original draft, Review;

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