

From ICT Literacy to AI-Ready Empowerment: An Explainable Fuzzy AHP–TOPSIS Framework for Women’s Digital Inclusion in Chhattisgarh

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Abstract

Digital empowerment is increasingly a prerequisite for meaningful participation in AI-enabled education, public services, employment, and civic life. Yet technology-oriented training can produce uneven benefits across different dimensions of empowerment. This study develops an explainable hybrid Fuzzy Analytical Hierarchy Process (F-AHP)–Fuzzy Technique for Order Preference by Similarity to Ideal Solution (F-TOPSIS) framework to evaluate women’s digital empowerment using evidence from selected ICT training programmes in Korba district, Chhattisgarh, India. The empirical base comprises 150 women trainees and 50 instructors and evaluates seven dimensions: technological, educational, economic, psychological, social, personal, and political empowerment. F-AHP is used to derive criterion importance under linguistic uncertainty, while F-TOPSIS estimates each dimension’s relative closeness to an ideal empowerment condition. To strengthen interpretability, the paper adds cross-method rank agreement and rank-margin diagnostics using the reported model outputs. Technological empowerment records the highest F-AHP weight (0.187) and F-TOPSIS closeness coefficient (0.822), followed by educational (0.804) and economic (0.778) empowerment. The AHP and TOPSIS orderings show very strong agreement (Spearman $\rho = 0.964$; Kendall $\tau = 0.905$), while the smallest adjacent TOPSIS margin occurs between psychological and social empowerment (0.012), indicating that middle-rank ordering should be interpreted cautiously. The resulting framework is positioned as an explainable decision-support tool for inclusive digital-skills programmes and AI-readiness planning rather than as a causal measure of empowerment. The study contributes a transparent pathway from ICT training evaluation to responsible, inclusion-oriented AI governance and digital citizenship.

Keywords: Women Empowerment; ICT Education; AI Readiness; Fuzzy AHP; Fuzzy TOPSIS; Explainable Decision Support; Digital Inclusion; Chhattisgarh.

1. Introduction

Artificial intelligence is becoming embedded in education, public administration, financial services, healthcare, labour markets, and citizen-facing digital platforms. Participation in these systems presupposes more than device ownership: users need digital literacy, confidence, access to information, and the ability to translate technical capability into educational, economic, social, and civic agency. For

women in semi-urban and rural settings, this transition makes digital empowerment an important precondition for equitable participation in emerging AI-enabled ecosystems.

This study builds on aggregated results from an ICT-training survey conducted in Korba district, Chhattisgarh, involving 150 women trainees and 50 instructors. Seven empowerment dimensions are examined through a hybrid fuzzy multi-criteria decision-making (MCDM) framework. The analysis extends the original ranking outputs by interpreting them through an AI-readiness and inclusive-governance lens, while explicitly avoiding any claim that the underlying training programme itself delivered AI instruction. Particular attention is given to agreement between the F-AHP and F-TOPSIS orderings and to small rank separations that may affect interpretation.

The problem is methodologically relevant because empowerment is multidimensional, perception-based, and context dependent. Conventional single-score approaches can conceal trade-offs among technological skills, education, livelihood opportunity, confidence, social participation, personal agency, and civic engagement. Fuzzy MCDM is appropriate when judgments are expressed linguistically and when a transparent rationale for prioritization is important. This transparency is also aligned with contemporary expectations for explainable and accountable decision support in AI-related governance contexts.

The paper makes four contributions. First, it retains the seven-dimensional ICT empowerment framework and repositions it as an AI-readiness lens without claiming that the original training programme itself used AI. Second, it separates expert-derived importance (F-AHP) from outcome proximity (F-TOPSIS), improving conceptual clarity. Third, it adds rank-agreement diagnostics—Spearman's rho and Kendall's tau—to quantify consistency between the two stages. Fourth, it introduces adjacent rank-margin analysis to identify dimensions whose ordering is comparatively fragile. Together, these additions turn a simple ranking exercise into a more interpretable decision-support framework suitable for programme design, digital inclusion strategy, and future responsible-AI capacity building.

2. Related Work and Research Gap

2.1 ICT, Digital Inclusion, and Women's Empowerment

Research on the gendered digital divide has consistently shown that access, skills, meaningful use, and socio-economic context interact in complex ways. Hilbert [1] argued that the digital gender divide cannot be understood only through access statistics because technology use is shaped by employment, education, income, and social conditions. Antonio and Tuffley [2] similarly emphasized that digital exclusion in developing contexts is reinforced by structural and socio-cultural constraints. These findings support multidimensional assessment rather than a binary connected/not-connected view of digital inclusion.

For training programmes, the critical question is therefore not merely whether participants learn to use devices or software, but whether skills translate into broader educational, economic, psychological, social, personal, and civic outcomes. In this respect, ICT education can be treated as an enabling layer whose effects may appear at different strengths and timescales across empowerment dimensions. A structured prioritization method can help programme designers identify where training has its strongest alignment and where complementary interventions may be required.

2.2 Fuzzy MCDM for Transparent Decision Support

The Analytical Hierarchy Process (AHP) provides a structured mechanism for eliciting relative importance through pairwise comparisons [3]. Fuzzy set theory [4] extends such judgments to situations

in which expert preferences are imprecise or linguistic. Chang's extent-analysis formulation [5] is widely used to derive fuzzy priorities, while TOPSIS ranks alternatives according to their distance from ideal and anti-ideal solutions. Chen's fuzzy extension of TOPSIS [6] is particularly suitable for group decision environments in which linguistic evaluations must be aggregated. Reviews of TOPSIS applications also show its broad use as a transparent and computationally accessible ranking method [7]. A recurring limitation in applied MCDM studies is that a final rank order is reported without enough attention to rank stability or the conceptual distinction between criterion importance and achieved outcome. This can encourage over-interpretation of small numerical differences. The present study addresses that gap by adding consistency and separation diagnostics to the hybrid F-AHP–F-TOPSIS pipeline.

2.3 Research Gap and Questions

The specific research gap is the lack of an explainability-oriented fuzzy MCDM interpretation of women's ICT empowerment that can support transition planning toward AI-enabled services while remaining faithful to the limits of cross-sectional survey evidence. The study therefore addresses three questions: (RQ1) Which empowerment dimensions receive the greatest importance and ideal-solution proximity? (RQ2) How consistent are the rankings produced by F-AHP and F-TOPSIS? (RQ3) Which adjacent ranks are most susceptible to reversal because their separation is small?

3. Materials and Methods

3.1 Study Context and Sample

The empirical basis consists of aggregated outputs from a structured questionnaire administered in selected ICT training programmes in Korba district. The underlying study covered 150 women trainees and 50 instructors and assessed seven dimensions of empowerment: technological, educational, economic, psychological, social, personal, and political. Responses were represented on a five-point linguistic scale and converted into triangular fuzzy numbers for the MCDM analysis. No new participant-level observations were collected for this manuscript; the additional explainability analyses use the available F-AHP weights and F-TOPSIS closeness coefficients.

3.2 Analytical Framework

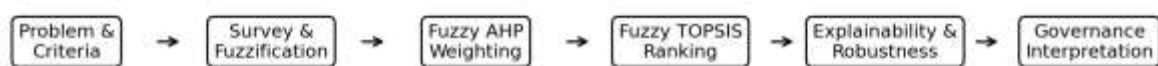


Figure 1. Explainability-oriented hybrid F-AHP–F-TOPSIS workflow for ICT empowerment and AI-readiness interpretation.

The framework has six stages. The first two define the multidimensional problem and encode survey/expert judgments as fuzzy values. F-AHP then estimates relative criterion importance, and F-TOPSIS calculates the proximity of each empowerment dimension to an ideal condition. A dedicated explainability stage evaluates cross-method rank agreement and adjacent score margins before the results are translated into programme and governance implications. This explicit separation is important:

F-AHP answers “what is considered important?”, whereas F-TOPSIS answers “which dimension is comparatively closest to the ideal state under the model?”.

3.3 Fuzzy AHP Weighting

Let a triangular fuzzy number be represented as $M = (l, m, u)$, where l , m , and u denote lower, modal, and upper values. Expert pairwise judgments are mapped to triangular fuzzy numbers, aggregated, and processed using the extent-analysis procedure. For criterion i , the fuzzy synthetic extent S_i is obtained from the fuzzy sum of row-wise judgments multiplied by the inverse of the overall fuzzy sum. Pairwise degrees of possibility are then used to obtain a normalized priority vector. The submitted study reports the final defuzzified weights shown in Table 1; these weights sum to 1.000.

S. No.	Empowerment dimension	F-AHP weight	Weight order
1	Technological	0.187	1
2	Educational	0.162	2
3	Economic	0.154	3
4	Social	0.131	4
5	Psychological	0.123	5
6	Personal	0.123	5*
7	Political	0.120	7

Table 1. Reported F-AHP weights. *Psychological and personal empowerment have equal weights (0.123).

3.4 Fuzzy TOPSIS Ranking

In F-TOPSIS, aggregated fuzzy evaluations are normalized and multiplied by the F-AHP weights. A fuzzy positive ideal solution (FPIS) and fuzzy negative ideal solution (FNIS) are constructed. For each empowerment dimension i , the closeness coefficient is computed as $CC_i = D_i^- / (D_i^+ + D_i^-)$, where D_i^+ and D_i^- denote distances from FPIS and FNIS, respectively. Larger CC values indicate greater relative proximity to the ideal empowerment condition. Importantly, CC is a model-based comparative measure and should not be interpreted as a causal effect size.

3.5 Explainability and Robustness Diagnostics

Three diagnostics are added to improve interpretation. First, Spearman’s rank correlation (ρ) measures monotonic agreement between the F-AHP and F-TOPSIS orderings. Second, Kendall’s tau (τ) measures concordance based on pairwise rank relationships. Third, an adjacent rank margin $\Delta_i = CC_i - CC_{i+1}$ is calculated for each pair of neighbouring TOPSIS ranks. A small Δ indicates that a modest change in model inputs could plausibly exchange the order of the two adjacent dimensions. These diagnostics do not replace full sensitivity analysis on the underlying fuzzy decision matrix; they provide a transparent, output-level stability check using the values available in the source study.

4 Results

4.1 F-TOPSIS Outcomes

Rank	Empowerment dimension	CC	Adjacent gap to next
1	Technological	0.822	0.018

Rank	Empowerment dimension	CC	Adjacent gap to next
2	Educational	0.804	0.026
3	Economic	0.778	0.022
4	Psychological	0.756	0.012
5	Social	0.744	0.016
6	Personal	0.728	0.019
7	Political	0.709	—

Table 2. F-TOPSIS closeness coefficients and adjacent rank margins.

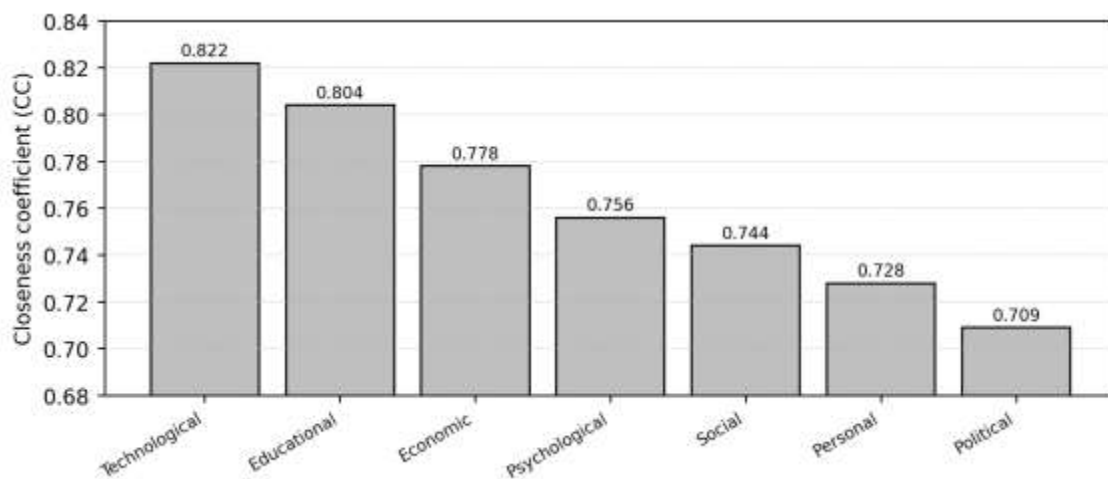


Figure 2. Closeness coefficients for the seven empowerment dimensions.

Technological empowerment ranks first (CC = 0.822), followed by educational (0.804) and economic (0.778) empowerment. Psychological (0.756) and social (0.744) empowerment occupy the middle of the distribution, while personal (0.728) and political (0.709) empowerment are comparatively farther from the ideal solution. The overall spread is 0.113, indicating meaningful but not extreme separation across the seven dimensions.

4.2 Cross-Method Consistency

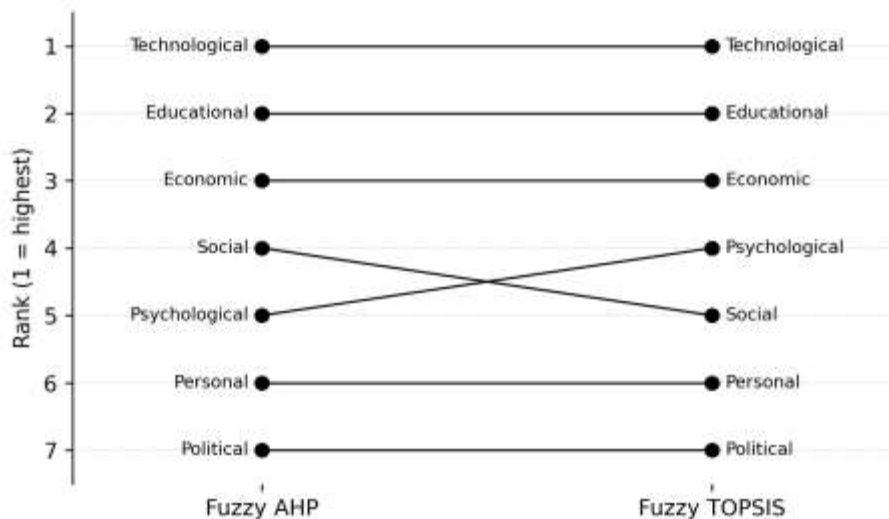


Figure 3. Rank agreement between F-AHP importance and F-TOPSIS outcome ordering.

The two methods produce nearly identical orderings. Technological, educational, and economic empowerment occupy the first three positions in both stages; personal and political empowerment also retain their positions. Only social and psychological empowerment exchange adjacent places. Using the reported ranks, Spearman's ρ is 0.964 and Kendall's τ is 0.905, indicating very strong cross-method agreement. These exact values strengthen the earlier qualitative claim of broad consistency and provide a reproducible internal validation check.

4.3 Rank-Margin Interpretation

The smallest adjacent TOPSIS gap is 0.012 between psychological and social empowerment. Under a simple symmetric perturbation interpretation, a change of approximately 0.006 in opposite directions would be sufficient to reverse their order. The next-smallest gaps are 0.016 (social–personal), 0.018 (technological–educational), and 0.019 (personal–political). Consequently, the middle ordering should be treated as a priority band rather than as a rigid league table. In contrast, the broader conclusion that technological and educational empowerment form the leading pair is supported by both weighting and ranking stages.

5 Discussion

5.1 What the Ranking Means for AI Readiness

The strongest results are concentrated in technological and educational empowerment. In an AI-readiness context, these dimensions are foundational because users must first possess operational digital capability, information-seeking skills, and learning confidence before they can meaningfully engage with AI-supported education, e-governance, legal information systems, automated service interfaces, or digital financial tools. The present data do not show AI adoption itself; rather, they identify the empowerment conditions most closely aligned with readiness for increasingly AI-mediated environments.

Economic empowerment ranks third, suggesting that skill acquisition may be connected to livelihood-oriented possibilities, although the cross-sectional design does not establish employment or income causality. This distinction is important for responsible programme evaluation. A training provider should separately measure digital competence, job transitions, entrepreneurship, income change, and persistence of outcomes over time rather than treating one composite score as proof of economic impact.

5.2 Explainability as a Governance Requirement

For public or institutional decision support, a ranking should be accompanied by an explanation of how it was produced, how stable it is, and what it does not imply. The present framework offers three explainability layers: criterion importance through F-AHP, outcome proximity through F-TOPSIS, and stability through rank agreement and separation margins. This is a useful design principle for future AI-assisted programme management systems because automated recommendations should not hide value judgments inside opaque scores.

The very small gap between psychological and social empowerment illustrates why explainability matters. Reporting only “rank 4” and “rank 5” could suggest a stronger distinction than the data justify. Margin analysis reveals that these positions are close and may change under modest perturbations. For governance, this supports grouped priority categories and transparent uncertainty communication rather than deterministic claims.

5.3 Digital Citizenship, Inclusion, and Broader Governance

Political empowerment receives the lowest TOPSIS coefficient in the model, but this does not mean that ICT education lacks civic value. The result is better interpreted as evidence that a technically oriented training programme is less directly aligned with civic participation than with technology use or education. If programme objectives include digital citizenship, rights awareness, e-governance access, grievance mechanisms, or participation in local institutions, these components should be explicitly designed and measured rather than assumed to arise automatically from technical training.

This interpretation connects the study to inclusive AI governance. As public services become more data-driven and algorithmically mediated, exclusion can occur not only through lack of connectivity but also through limited digital confidence, inability to understand automated decisions, weak access to redress, or insufficient awareness of data and privacy rights. Women's digital empowerment initiatives can therefore serve as a bridge between basic ICT skills and meaningful participation in AI-enabled governance, provided that technical instruction is complemented by rights, safety, privacy, and accountability content.

6 Practical Framework for Training and Policy Design

Dimension	Programme component for AI-ready inclusion	Planning role
Technological	Core digital operations, cybersecurity hygiene, AI tool literacy	Immediate capability
Educational	Information literacy, critical evaluation, AI-assisted learning	Continuous learning
Economic	Digital work, entrepreneurship, platform literacy	Livelihood linkage
Psychological	Confidence, self-efficacy, safe experimentation	Adoption support
Social	Peer networks, collaborative learning, community applications	Social diffusion
Personal	Decision support, autonomy, household-level digital agency	Agency building
Political	E-governance, rights awareness, grievance/redress channels	Digital citizenship

Table 3. Dimension-linked programme design implications derived from the ranking framework.

Table 3 should be read as a design translation, not as an additional empirical result. It shows how the seven dimensions can be connected to future AI-ready digital inclusion programmes. The key principle is modularity: technology and education can remain the core, while livelihood, confidence, social

support, autonomy, and civic-rights modules are added according to programme objectives and local needs.

7 Limitations and Validity Considerations

The study has several limitations. The sample is restricted to selected ICT training programmes in Korba district and therefore should not be generalized to all women in Chhattisgarh or India. The design is cross-sectional and cannot establish causal impact. The source manuscript does not report participant-level data, psychometric reliability coefficients, a detailed expert-panel profile, or a full perturbation analysis of the fuzzy decision matrix. Consequently, the additional robustness checks in this paper are output-level diagnostics rather than substitutes for resampling, weight perturbation, or external validation.

A second limitation is conceptual. “AI readiness” is an interpretive extension of the ICT empowerment results, not a directly measured construct in the underlying survey. Future work should therefore include AI-specific items such as understanding of automated systems, safe and critical use of generative AI, privacy awareness, ability to contest automated outcomes, bias awareness, and confidence in using AI-enabled public services. Such indicators would allow the present framework to evolve from ICT empowerment assessment into a validated AI-readiness instrument.

8 Conclusion and Future Work

This paper presents an explainable hybrid F-AHP–F-TOPSIS framework for interpreting women’s ICT empowerment as a foundation for AI-ready digital inclusion. Using the reported Korba district study of 150 women trainees and 50 instructors, the analysis confirms that technological and educational empowerment are the strongest dimensions, followed by economic empowerment. The addition of rank-agreement diagnostics shows very strong consistency between F-AHP and F-TOPSIS (Spearman $\rho = 0.964$; Kendall $\tau = 0.905$), while adjacent margin analysis identifies psychological and social empowerment as the least separated pair. These diagnostics make the model more transparent and reduce the risk of over-reading small rank differences.

The principal implication is that digital-skills programmes should not treat empowerment as a single outcome. A technically strong programme may still require complementary interventions for livelihood conversion, confidence, social participation, personal agency, and digital citizenship. For future AI-enabled governance, this multidimensional view is especially important: access to AI tools will be equitable only when users also possess the capabilities and rights awareness needed to use, question, and benefit from them. Future studies should validate the questionnaire across multiple districts, report reliability and expert-selection procedures, test weight sensitivity, compare alternative MCDM methods, and collect longitudinal AI-specific outcome measures.

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