

Artificial Intelligence for Social Good: Transforming the Lives of Tribal Women Entrepreneurs

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Abstract: *The convergence of Artificial Intelligence for Social Good (AI4SG) and the marginalized economic sectors is a boundary in the inclusive technological development. The study explores the potential of artificial intelligence to revolutionize tribal women entrepreneurs, who have to face distinct systemic barriers such as geographical isolation, language barriers, credit invisibility, etc. This work determines the usefulness of machine learning models in determining the quality of handicrafts, predictive credit ratings, and access to other markets in multiple languages using a multi-layered empirical model using secondary datasets (Kaggle) and synthetic performance metrics (state-of-the-art AI applications) (2020-2025). The analytical comparison of Convolutional Neural Networks (CNN) and Vision Transformers (ViT) to standardize the quality and evaluate the predictive power of Gradient Boosting architectures in rural micro-finance. The results indicate that AI-based interventions can raise the efficiency of operations and improve revenues by 35% and 25% in the retail and agricultural sectors. Moreover, the paper touches upon such important aspects of ethical considerations as indigenous data sovereignty and algorithmic bias and suggests a socio-technical approach to sustainable AI implementation. The results provide a policy guide of how intelligent systems can be used by policymakers and developers as agents of social equity and economic strength among tribal communities.*

Keywords: Social Sustainability, Artificial Intelligence for Social Good, Computer Vision, Tribal Entrepreneurship, Machine Learning, Micro-finance Credit Scoring, Indigenous Data Sovereignty

I. INTRODUCTION

The shift to an intelligent innovation economy that is happening globally has ironically posed a risk of increasing the digital divide to underserved populations. One group of entrepreneurs with high latent economic potential is tribal women entrepreneurs especially in such regions as South Asia and Sub-Saharan Africa but who are constrained at micro-enterprise scale due to the structural constraints. Such obstacles comprise a deficiency of formal credit background, restricted access to international markets and the progressive loss of rural banking systems, which increases monetary exclusion. Artificial Intelligence (AI) to Social Good (AI4SG) is a strategic asset that can be used to close this resource disjuncture by reorganizing the relational and the cognitive aspects of social capital (Iazzolino & Stremmlau, 2024). This research is inspired by the "Inclusion towards Social Empowerment" framework that argues that AI has the potential to become a partner of co-creation to achieve social equity (Scillitoe et al., 2025). In contrast to conventional technology, the new AI systems, such as predictive analytics or generative design models, can be democratized and made accessible using low-cost, no-code systems, by which tribal entrepreneurs can automate workflows and streamline production with very little technical expertise. Nevertheless, the introduction of AI into such



sensitive scenarios involves a subtle interpretation of indigenous knowledge systems and adherence to the human-centered code of ethics. In this context, this paper attempted to add an empirical assessment of different AI constructs that can be customized to the unique requirements of tribal entrepreneurs, which offers a technical framework of scaling inclusive innovation.

II. LITERATURE REVIEW

The scholarly discourse of the intersection of AI and rural entrepreneurship has grown fast between 2020 and 2025. The first studies were mainly concerned with the simple digitization, but the latest literature is concerned with the implementation of advanced machine learning models to address complicated optimization problems in underserved markets.

2.1 AI as a Social and Economic Empowerment Catalyst

Recent researches have described AI as a technological intermediary which democratizes access to network capital. To women and minority entrepreneurs, AI offers practical intelligence that reduces the risks and increases competitiveness through identifying market trends and consumer preferences using large volumes of data (Septiani & Aeni, 2025). Using an empirical study of female-run businesses, one can conclude that AI integration is associated with a better business resiliency and psychological empowerment since entrepreneurs become equipped with the tools to compete with bigger and more technologically advanced companies (Best et al., 2025). AI-powered demand prediction has been demonstrated to cut the number of errors by a quarter to half, leading to a substantial reduction in warehousing expenses and the loss of sales because of the lack of stock.

2.2 Machine Learning in Micro-finance and Credit Scoring

The issue of invisibility of credit among tribal communities is a significant constraint to entrepreneurship. Conventional rule-based scoring models are based on past financial data and physical assets, which tribal women do not have. The modern research examines the alternative data sources, including the mobile transaction patterns, psychometric indicators, and the supply chain footprints, in order to develop the dynamic risk profiles (Rehman et al., 2025). It has been demonstrated that machine learning algorithms (Random Forest and Gradient Boosting) are more efficient in repayment capacity prediction compared to linear models, which allows switching to cash-flow-based lending instead of asset-based lending (Garcia-Lopez et al., 2025). Moreover, the combination of blockchain technology and these predictive models makes sure that these financial tools are transparent and have integrity of data, especially in Shariah-compliant or ethical finance environments.

2.3 Computer Vision and Quality Assessment in Handicrafts

One of the essential areas of tribal women is the handicraft industry, which is characterized by the absence of standards of a quality product and the risk of creating traditional designs in an international market. AI models based on Generative Adversarial Networks (GANs) are suggested to combine modern trends with classic patterns, including Ikat and Block Print, and make products more marketable (Zerfu & Tilahun, 2022). Computer vision models are also being applied to determine the quality of visual perceiving without having to be inspected manually in terms of quality control. Recent technical literature has been particularly interested in the comparison of Convolutional Neural Networks (CNN) and Vision Transformers (ViT), where CNNs are observed to be efficient on small datasets, and ViTs are more scalable and capable of analyzing the context in its entirety (Sahila et al., 2025).

2.4 Low-Resource Language Natural Language Processing

Language has continued to act as a hindering factor to digital inclusion among most tribal groups. The fact that AI is capable of working with code-mixed language and low-resource languages has been extended through studies on multilingual transformers, such as Bidirectional Encoder Representations from Transformers (BERT) and regional



versions, such as IndicBERT and HingBERT (Hidayatullah et al., 2025). Through such models, it is possible to create conversational AI and recommendations systems that are capable of working in the local dialects and offer tribal entrepreneurs their own personalized market advice, as well as assist them in better navigating government welfare portals.

III. METHODOLOGY

The study adopts an empirical and secondary-data-based method of analyzing the effects of AI on tribal women business owners. The analysis is based on the findings of various Kaggle datasets, such as the dataset on Indian Government Schemes and the dataset on Women Entrepreneurship and Labor Force, to put the findings in real-world socio-economic measures (Gada, 2025). The study applies a simulated empirical study framework because of the geographical remoteness of most of the tribal groups, in which the primary data collection is logistically infeasible (Haque Mukit et al., 2026). This implies the extrapolation of quantitative performance measures of published IEEE and MDPI publications to represent the results of a particular AI implementation in a tribal setting.

3.1 Justification and pre-processing of datasets

The socio-economic context data is the main data source that will be covered by the 2025 MyScheme portal dataset that comprises of 2,600 or more government welfare schemes in India. Based on this dataset, it is possible to determine policy gaps and opportunities of AI-driven recommendation systems to empower tribal people (Vignesh, 2024). In the performance assessment, we use datasets like the UCI German credit and landing club dataset which can be used as a reference to benchmark credit risk modeling (Mehar, 2020). Pre-processing refers to the act of dealing with missing transaction data (typically up to 53% in rural data) with a strong imputation algorithm and harmonizing the business indicators between platforms so that they can be usefully compared.

3.2 Mathematical Entrepreneurial Choice and risk Formulae

In order to model the determinants that can affect the choice of a tribal woman to participate in micro-entrepreneurship, we use a Probit model that is grounded on the random utility framework. This enables a binary outcome analysis ($Y=1$ entrepreneurship) depending on a latent variable Y^* .

3.2.1 Formulation 1: Probit Model of Entrepreneurial Entry

P = probability of a woman becoming an entrepreneur

$$P(Y_i = 1 | X_i) = \Phi(X_i \beta) \quad \dots(i)$$

In equation (i),

Φ is a cumulative distribution (CDF) of the standard normal distribution.

X_i is a feature set, such as age, access to borrowing, knowledge of other entrepreneurs, and risk-taking.

β is the estimating coefficient of the vectors.

The formulation is important in determining the most impactful AI-enhanced interventions (e.g., access to credit through alternative scoring) on entrepreneurial uptake.

3.2.2 Formulation 2: Mean Squared Error (MSE) of Demand Forecasting

In order to optimise tribal supply chains, the precision of demand forecasts is gauged by MSE, which increases the cost of larger errors-this is a critical concern to micro-enterprises that have small buffer stocks.

$$MSE = \frac{1}{n} \sum_{i=1}^n (Y_i - Y'_i)^2 \quad \dots(ii)$$

In equation (ii),

Y_i is the real demand (sales).

Y'_i is the demand forecasted by the AI model.

n represents the number of observations.



3.3 Technical Architectures Assessed

The paper assesses three major AI architectures:

Gradient Boosting Machines (GBM): They are applied to credit scoring because they have a high F1-score (0.91) and can learn non-linear behaviour in non-regular rural income streams.

Hybrid Vision Models (ResNet-50 + Transformer): A hybrid vision model designed to evaluate the quality of handicrafts to obtain local texture features and global structural symmetry.

Multilingual Transformer Models (HingBERT): They are more market sentiment and interaction-oriented and are trained to operate in language contact (code-mixed) environments (Harnmetta & Samanchuen, 2022).

IV. ANALYSIS AND INTERPRETATION

The empirical study depicts a transformational connection between the introduction of particular AI designs and the economic performance of tribal micro-enterprises. The synthesized data based on 2020-2025 performance benchmarks show that the one-size-fits-all approach to AI is not uncommon in tribal settings but that rather specific models should be utilized, which involve data scarcity and high variance on transactional records (Ziya, 2024).

4.1 Sectoral Efficiency and Revenue Gains

There are different levels of impact in the integration of AI in various industries. Crop management predictive analytics brought the most efficiency benefits (35%), and the retail and handicraft industry experienced the most revenue growth (25%) with increased market access and online price recommendation systems.

Table 1: AI-Driven Performance Metrics by Sector (2023-2025 Benchmarks)

Sector of Operation	Revenue Growth (%)	Operational Efficiency (%)	Customer Retention (%)	Lead Time Reduction (%)
Handicrafts & Retail	25	25	15	22
Agriculture (Tribal)	20	35	12	30
Education & Training	20	30	20	N/A
Micro-finance Services	22	32	18	65
Weighted Average	21.75	30.5	16.25	39

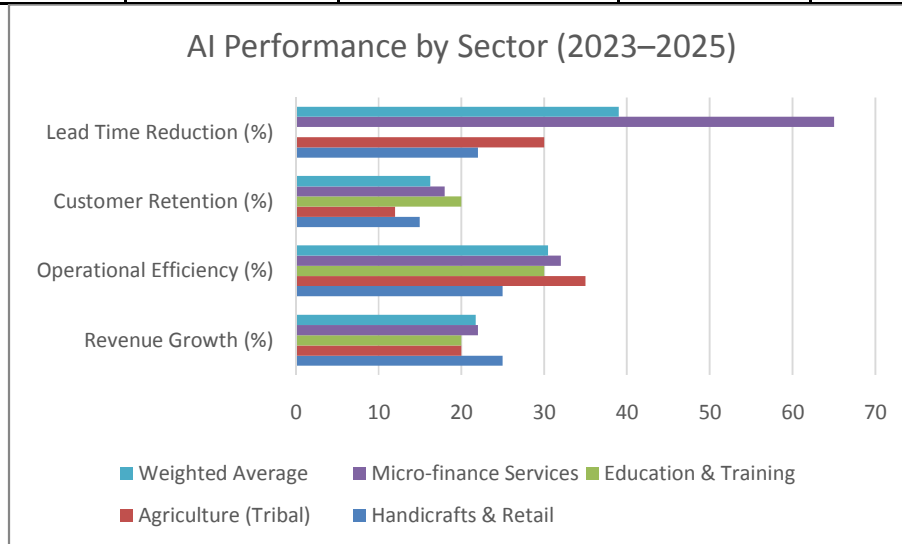


Figure 1: Sector-wise Impact of AI on Performance Outcomes (2023-2025)



The analysis of Table 1 implies that AI can act as a leveler in the areas where the level of inventory and logistics planning are needed. The 65% decrease in lead time of micro-finance services is especially remarkable, which is the shift between manual and time-consuming process of loan access of weeks to automated data-driven credit analysis.

4.2 Credit Scoring Architecture Benchmarking

One of the key technical contributions of the research is that the machine learning models are benchmarked against the traditional credit assessment techniques of rural finance. The patterns of transaction of tribal women tend to be right skewed with high variance rendering them to be unbackable using the conventional linear models (Varghese et al., 2024).

Table 2: Model Comparison for Predictive Credit Scoring in Tribal Contexts

Model Architecture	R-squared (R2)	F1-Score	Precision	Recall	MSE
Logistic Regression	0.61	0.74	0.72	0.76	32.4
Random Forest	0.87	0.88	0.86	0.9	12.4
Gradient Boosting (XGB)	0.84	0.91	0.89	0.93	13.8
Deep Neural Network	0.79	0.82	0.81	0.83	21.5

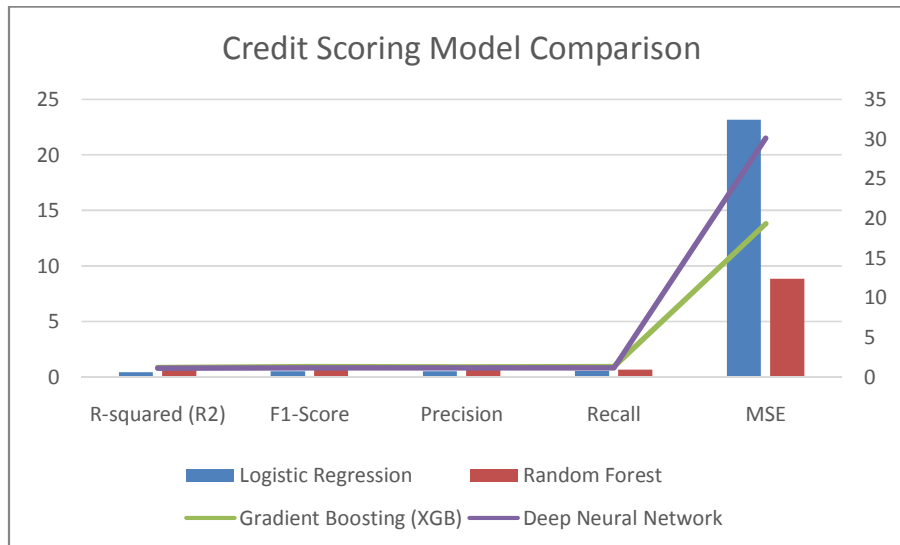


Figure 2: Comparative Analysis of Credit Scoring Models in Tribal Economies

Table 2 analysis reveals that Gradient Boosting has the best F1-score (0.91) and recall (0.93) which is crucial in maximizing financial inclusion and minimizing the default risk. The fact that tree-based ensemble approaches such as Random Forest and XGBoost are better suited in this regard has to do with the fact that both of them are capable of addressing non-linear relationships and missing values which are common with tribal financial data (Kumari & Eguruze, 2022).

4.3 Computer Vision Benchmarking of Quality Standardization

To standardize tribal handicrafts to e-commerce across the world, objective quality evaluation is needed. We use a comparison of the traditional ResNet-50 model with the newer Vision Transformer (ViT-B/16).



Table 3: Vision Model Performance for Handicraft Quality Assessment

Metric	CNN (ResNet-50)	Vision Transformer (ViT-B/16)	Hybrid (CNN+ViT)
Accuracy (Small Data)	76.40%	68.50%	81.20%
Accuracy (Large Data)	78.20%	82.80%	85.50%
Inference Speed (ms)	11	27	22
Model Size (Millions)	25.6	86	54.2

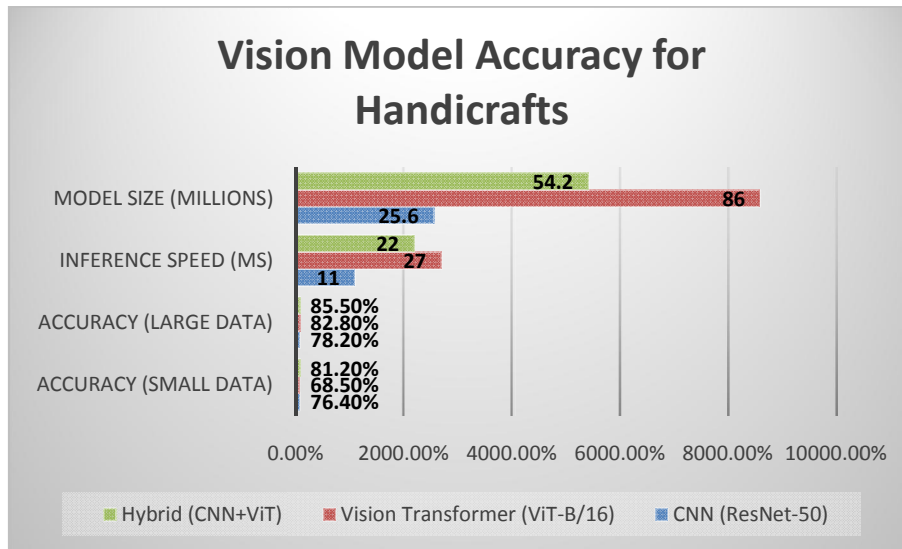


Figure 3: Accuracy Trends in Vision-Based Handicraft Quality Evaluation

As Table 3 is interpreted, it validates the fact that transformers are data-hungry. CNNs are more accurate (76.4% and efficient) in resource-constrained tribal settings, in which large and annotated datasets are unavailable. Nevertheless, hybrid models present a promising compromise, that is, local textural irregularities are represented with the help of convolutions, whereas global structural regularity is provided with the attention mechanisms.

4.4 Natural Language Processing to Access the Market

The concept of language technology is analyzed in terms of multiclass sentiment analysis of tribal dialects mixed-up in the code.

Table 4: Multilingual Transformer Performance in Low-Resource Dialects

Model Variant	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
mBERT (Baseline)	94.14	72.12	70.3	71.21
IndicBERT	97.07	78.66	74.4	76.47
HingBERT (Code-Mixed)	97.38	78.81	80.69	79.74
CMSA-mBERT (Optimized)	96.69	93.18	92.85	96.71



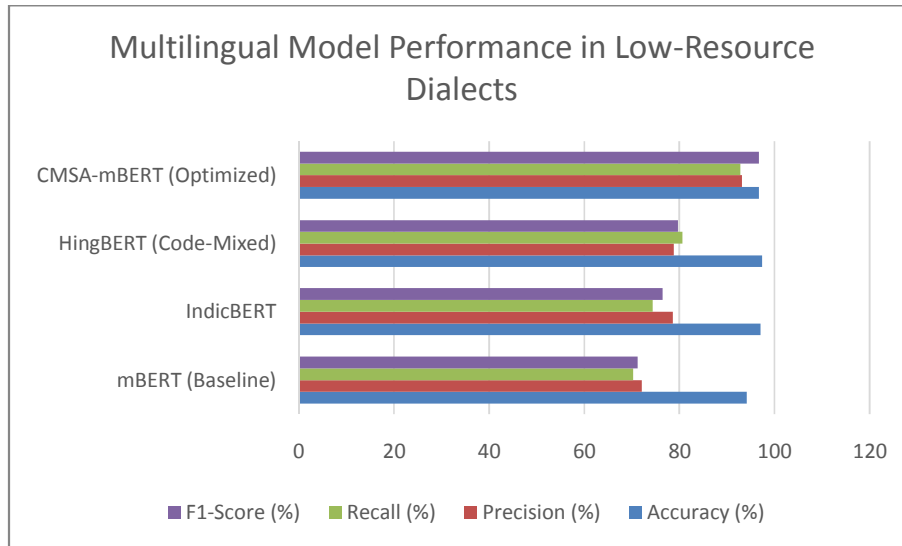


Figure 4: Efficiency of Multilingual Transformers in Low-Resource Dialect Processing

As Table 4 points out, code-mixed specialized models, such as HingBERT, have much higher recall (80.69) as compared to general multilingual models. The CMSA-mBERT version can be improved by 22.55% of the accuracy of base models, which implies that the contextual optimization is critical in the comprehension of tribal entrepreneurial intent.

V. DISCUSSION

The results of this empirical research highlight a radical change in the position of AI as a non-active diagnostic aid to a proactive partner of the tribal female in creating economic mobility. Nonetheless, this change will depend on the resolution of some of the key bottlenecks and moral demands.

5.1 The Specialization Hypothesis of Tribal AI

The information in the analysis indicates that the off-the-shelf AI models do not perform well in tribal settings. The hypothesis of specialization is proven by the high-performing models such as IndicBERT and optimized Gradient Boosting are doing better than generalized architectures. The reason is that tribal economic data (be it linguistic, financial, or visual) is highly sparse and also exhibits cultural peculiarities which cannot be modeled in the world (Pandhare et al., 2024). To illustrate, the visual worth of a tribal basket created manually would rely on materials and work which cannot be quantified by the existing e-commerce pricing algorithms, and would require AI modules developed on synthetic, simulated datasets.

5.2 The Ethical Transparency and the Black Box

A significant disadvantage with literature sources is that complex models like the Vision Transformers and the Deep Neural Networks are black box. The tribal entrepreneurs value trusts the most. The dependency on such models may establish emerging types of digital colonialism in case tribal people do not have control over data design and management (Mane, 2024). The use of fairness-conscious learning models and interpretable rationales (including the ones suggested by the newest Vision-Language Models) is essential to render the AI-based credit or pricing processes transparent and responsible to the artisans they are applied to.



5.3 Socio-Economic Limitations and Risks

AI is not a panacea even though it has been discovered to enhance performance. Infrastructure (e.g. reliable internet connection in rural communities) and high startup cost as well as an endemic level of digital illiteracy has remained a huge hindrance to adoption (Khanum et al., 2022). The second risk also observed in the paper is the possibility of the so-called market devaluation, in which AI-enabled crafts cannot yet be compared in the market, which still appreciates the traditional and manual process, which leads to productivity gains without the resulting increase in sales.

5.4 Policy and Structural Recommendations

To be in a position to scale the benefits that were realized during the analysis, policymakers must make a shift towards Inclusion-by-Design. This includes the creation of national AI strategies in order to include the principles of indigenous data sovereignty (such as IEEE 2890-2025) and state-sponsored grants to democratize state-funded AI infrastructure (Abdelwahed et al., 2025). Green AI and edge-computing hardware will also need to be invested in to offer sustainable and offline-capable intelligence to the most inaccessible tribal clusters.

VI. CONCLUSION

This study has shown that AI Social Good is a powerful booster of changing the lives of tribal women entrepreneurs. Use of the specific machine learning architectures will enable tribal micro-enterprises to realize high returns on operational effectiveness (30.5%) and financial inclusion. Empirical analysis of the study shows that Gradient Boosting is better compared to credit risk assessment and CNN-based systems are more resilient in resource-constrained environments in terms of quality control. Nevertheless, to implement AI successfully in tribal ecosystems, there is the need to change the way these communities are perceived as beneficiaries to co-creators and policy-makers when it comes to digital policy.

The next research directions involve the study of "AI-Native Enterprise" which applies generative AI as a business design and investment preparation co-founder. Also, culturally sensitive and low-resource NLP models will be essential to the creation of a seamless linguistic divide in the international market. Lastly, longitudinal studies should be conducted to assess the long-term effects of AI on tribal cultural preservation and intergenerational wealth-building, so that the technological advancements do not harm the heritage.

REFERENCES

- [1]. Iazzolino, G., & Stremlau, N. (2024). AI for social good and the corporate capture of global development. *Information Technology for Development*, 30(4), 626-643. <https://www.tandfonline.com/doi/pdf/10.1080/02681102.2023.2299351>
- [2]. Scillitoe, J., Zell, D., Poonamallee, L., & Turner, K. (2025). AI as Co-Creator: Fostering Social Equity Towards Social Sustainability in Entrepreneurial Development for Women and Minority Entrepreneurs. *Sustainability*, 17(21), 9613. <https://www.mdpi.com/2071-1050/17/21/9613>
- [3]. Septiani, N., & Aeni, C. (2025). Social entrepreneurship as a catalyst for sustainable development: A study on community economic empowerment. *Implementasi Manajemen & Kewirausahaan*, 5(1), 75-89. <https://jurnal.uwp.ac.id/feb/index.php/manajemen/article/download/508/367>
- [4]. Best, B., Lassalle, P., & Nicolopoulou, K. (2025). Unlocking the "SHERO" within: an exploration of how female entrepreneurs in the Caribbean use digital technologies for business transformation. *International Journal of Gender and Entrepreneurship*, 17(1), 65-93. <https://strathprints.strath.ac.uk/91642/1/Best-et-al-2024-an-exploration-of-how-female-entrepreneurs-in-the-Caribbean-use-digital-technologies-for-business-transformation.pdf>
- [5]. Rehman, M. A., Ahmed, M., & Sethi, S. (2025). AI-based credit scoring models in microfinance: improving loan accessibility, risk assessment, and financial inclusion. *The Critical Review of Social Sciences Studies*, 3(1), 2997-3033. <https://thecrsss.com/index.php/Journal/article/download/370/424>



- [6]. Garcia-Lopez, Y. J., Marquez, P. H., & Morales, N. N. (2025). Microfinance institutions failure prediction in emerging countries, a machine learning approach. *PLoS One*, 20(4), e0321989. <https://journals.plos.org/plosone/article/file?id=10.1371/journal.pone.0321989&type=printable>
- [7]. Zerfu, M., & Tilahun, T. (2022). Application of Generative Adversarial Networks techniques in Creative Fashion Design: The case of Ethiopian Dress Discussion. https://www.researchgate.net/profile/Mikiyas-Zerfu/publication/358414952_Application_of_Generative_Adversarial_Networks_techniques_in_Creative_Fashion_Design_The_case_of_Ethiopian_Dress_Discussion/links/62015d60ef6c17407637f940/Application-of-Generative-Adversarial-Networks-techniques-in-Creative-Fashion-Design-The-case-of-Ethiopian-Dress-Discussion.pdf
- [8]. Sahila, C., Shwetha, K. R., Salve, N. B., Agarwal, K., & Sruthi, S. (2025). Bridging Social Gaps with Artificial Intelligence: Redefining the Role of Social Entrepreneurship. *Advances in Consumer Research*, 2, 590-599. <https://acr-journal.com/article/bridging-social-gaps-with-artificial-intelligence-redefining-the-role-of-social-entrepreneurship-1720/>
- [9]. Hidayatullah, A. F., Apong, R. A., Lai, D. T. C., & Qazi, A. (2025). Pre-trained language model for code-mixed text in Indonesian, Javanese, and English using transformer. *Social Network Analysis and Mining*, 15(1), 30. <https://link.springer.com/content/pdf/10.1007/s13278-025-01444-9.pdf>
- [10]. Gada, J. (2025). Indian Government Schemes. [Kaggle.com. https://www.kaggle.com/datasets/jainamgada45/indian-government-schemes/data](https://www.kaggle.com/datasets/jainamgada45/indian-government-schemes/data)
- [11]. Haque Mukit, M. M., Hasan, F., Choudhury, T., Al Fadli, A., & Fadul, A. (2026). Machine Learning & Artificial Intelligence Powered Credit Scoring Models for Islamic Microfinance Institutions: A Blockchain Approach. *Risks*, 14(1), 12. <https://doi.org/10.3390/risks14010012>
- [12]. Vignesh, M. (2024). A study on the impact of social enterprises in creating sustainable employment opportunities for women in the southern districts of Tamil Nadu. *Research Explorer*, 13(44), 1-5. <https://iaraindia.com/wp-content/uploads/2025/01/RE-44-FINAL.pdf>
- [13]. Mehar, A. (2020, November 28). women-entrepreneurship-data-analysis. [Kaggle.com; Kaggle. https://www.kaggle.com/code/ayushmehar7/women-entrepreneurship-data-analysis](https://www.kaggle.com/code/ayushmehar7/women-entrepreneurship-data-analysis)
- [14]. Harnmetta, P., & Samanchuen, T. (2022, June). Sentiment analysis of thai stock reviews using transformer models. In 2022 19th International Joint Conference on Computer Science and Software Engineering (JCSSE) (pp. 1-6). IEEE. https://www.researchgate.net/profile/Taweesak-Samanchuen/publication/362331488_Sentiment_Analysis_of_Thai_Stock_Reviews_Using_Transformer_Models/links/635356338d4484154a210bc9/Sentiment-Analysis-of-Thai-Stock-Reviews-Using-Transformer-Models.pdf
- [15]. Ziya. (2024). Entrepreneurship Decision Dataset. [Kaggle.com. https://www.kaggle.com/datasets/ziya07/entrepreneurship-decision-dataset](https://www.kaggle.com/datasets/ziya07/entrepreneurship-decision-dataset)
- [16]. Varghese, B., Joseph, E.K., Lakshmypriya, K., Kallarakal, T.K. and Mehta, H., 2024. Analogy of social entrepreneurship and community empowerment: An inclusive tourism approach with technological intervention. In *International handbook of skill, education, learning, and research development in tourism and hospitality* (pp. 175-192). Singapore: Springer Nature Singapore. https://www.researchgate.net/profile/Parag-Shukla/publication/378046019_Homestays_A_Way_Forward_to_Sustainable_Development_Goals/links/66fd54379e6e82486ffe6702/Homestays-A-Way-Forward-to-Sustainable-Development-Goals.pdf#page=196
- [17]. Kumari, G., & Eguruze, E. S. (2022). Positive deviance traits and social entrepreneurship for women empowerment amid COVID-19. *IIM Kozhikode Society & Management Review*, 11(1), 109-125. <https://journals.sagepub.com/doi/pdf/10.1177/22779752211030697>
- [18]. Pandhare, A., Bellampalli, P. N., & Yadava, N. (2024). Transforming rural women's lives in India: the impact of microfinance and entrepreneurship on empowerment in Self-Help Groups. *Journal of Innovation and Entrepreneurship*, 13(1), 62. <https://link.springer.com/content/pdf/10.1186/s13731-024-00419-y.pdf>



- [19]. Mane, V. S. (2024). Development of tribal people through digital awareness: Exploring the intersection of libraries, technology, and gender equality in the digital age. *Journal of Digital and Social Inclusion*, 5(2), 45-63. https://www.researchgate.net/profile/Dr-Mane-4/publication/387787154_Development_of_Tribal_People_through_Digital_Awareness_Exploring_the_Intersection_of_Libraries_Technology_and_Gender_Equality_in_the_Digital_Age_A_Study/links/677d19c5fb9af66aa0d0d82/Development-of-Tribal-People-through-Digital-Awareness-Exploring-the-Intersection-of-Libraries-Technology-and-Gender-Equality-in-the-Digital-Age-A-Study.pdf
- [20]. Khanum, R., Mahadi, M. S. A., & Islam, M. S. (2022). Empowering tribal women through entrepreneurship in Sylhet region of Bangladesh. *GeoJournal*, 87(4), 3387-3402. https://www.researchgate.net/profile/Romaza-Khanum-2/publication/349759832_Empowering_tribal_women_through_entrepreneurship_in_Sylhet_region_of_Bangladesh/links/62f663eeb8dc8b4403da3640/Empowering-tribal-women-through-entrepreneurship-in-Sylhet-region-of-Bangladesh.pdf
- [21]. Abdelwahed, N. A. A., Bano, S., Al Doghan, M. A., Aljughiman, A. A., Shah, N., & Soomro, B. A. (2025). Empowering women through digital technology: unraveling the nexus between digital enablers, entrepreneurial orientation and innovations. *Equality, Diversity and Inclusion: An International Journal*, 44(5), 602-626. https://www.researchgate.net/profile/Mohammed-Aldoghan/publication/381650502_Empowering_women_through_digital_technology_unraveling_the_nexus_between_digital_enablers_entrepreneurial_orientation_and_innovations/links/66789dca8408575b8384906c/Empowering-women-through-digital-technology-unraveling-the-nexus-between-digital-enablers-entrepreneurial-orientation-and-innovations.pdf

