

Artificial Intelligence in CSR Evaluation: A Community-Centred Social Work Perspective

Manju Vaishnavi.V¹, Dr. R. Baskar²

¹ Research Scholar, Department of Social Work, Bharathiar University

² Head & Associate Professor, Department of Social Work, Bharathiar University

Abstract

Corporate Social Responsibility (CSR) in India has gradually moved beyond traditional philanthropy towards a more structured form of corporate engagement in social and environmental development. As CSR initiatives expand, greater attention is being given to evaluating whether these interventions produce meaningful and sustainable outcomes for communities. Conventional evaluation methods often focus on expenditure, activities completed, beneficiary numbers, and organisational reports. Although these indicators are useful, they may not fully capture changes in community well-being, participation, inclusion, and sustainability. The growing availability of digital information has created opportunities for Artificial Intelligence (AI) to strengthen CSR evaluation through data analytics, Natural Language Processing (NLP), continuous monitoring, pattern identification, predictive analysis, and ESG reporting. However, AI-assisted evaluation also raises concerns relating to data quality, fragmented standards, algorithmic bias, privacy, transparency, digital exclusion, and the difficulty of representing complex social experiences through numerical indicators. This paper examines the emerging role of AI in CSR evaluation from a community-centred social work perspective. It discusses the applications, opportunities, and limitations of AI and emphasises the need to combine technological analysis with community participation and professional judgement. Based on the literature reviewed, the paper proposes a five-stage community-centred AI-assisted CSR evaluation framework comprising clear CSR objectives, multiple sources of evidence, AI-assisted analysis, community and professional validation, and evidence-based programme improvement. The paper argues that responsible AI-assisted evaluation should contribute not only to better reporting and monitoring but also to more responsive, transparent, inclusive, and meaningful CSR interventions.

Keywords: Artificial Intelligence, CSR evaluation, Natural Language Processing.

1. Introduction

Corporate Social Responsibility (CSR) has become an increasingly important part of the relationship between business and society. In India, the introduction of Section 135 of the Companies Act, 2013 created a formal regulatory framework for CSR among eligible companies. This development encouraged corporate organisations to contribute to areas such as education, healthcare, livelihoods, environmental protection, and community development. Afaq and Maryam (2024) describe the Indian CSR mandate as an important shift in the relationship between corporate activity and social responsibility.

However, an increase in CSR expenditure does not necessarily mean that social impact has increased to the same extent. Recent discussions on CSR in India point to uneven geographical and sectoral distribution of CSR spending, along with concerns about compliance-oriented approaches. Ghorpade and Mandal (2025), for example, argue that the growth in aggregate CSR expenditure has not always been accompanied by equally strong community-driven interventions or independent impact evaluation. This raises an important question: should CSR success be judged mainly by whether companies have spent the required amount, or by whether those resources have contributed to meaningful changes in communities? This makes CSR evaluation particularly important. Counting beneficiaries, recording activities, and reporting expenditure can show whether a programme has been implemented, but such measures may not adequately explain whether the intervention has improved people's lives. Kumar et al. (2025), through an impact evaluation of CSR initiatives undertaken by sugar mills in Northern India, demonstrate the importance of examining socioeconomic outcomes rather than focusing only on programme expenditure. Their study, based on survey data from 571 farmers, identified changes associated with agricultural practices, water use, livelihoods, and other socioeconomic outcomes.

At the same time, CSR programmes are generating increasingly large amounts of digital information. Companies, NGOs, government agencies, and communities produce information through programme databases, surveys, reports, social media, websites, monitoring systems, and other digital platforms. This development has created new possibilities for Artificial Intelligence (AI) to support CSR monitoring and evaluation. Recent literature suggests that AI can contribute to CSR through analytics, automation, monitoring, ESG reporting, and decision support. Kaleem et al. (2025) examine the relationship between CSR, AI, and financial performance and identify AI-enabled analytics and automation as emerging areas of CSR practice. Shrivastava (2025) similarly discusses the potential of AI to improve the efficiency of CSR activities while drawing attention to concerns relating to privacy, security, and algorithmic bias.

AI is particularly relevant to CSR evaluation because conventional measurement approaches have several limitations. Kolekar et al. (2025) point out that traditional methods may depend heavily on company-reported information and may provide limited real-time or third-party perspectives. Their proposed AI-powered CSR evaluation system uses Natural Language Processing (NLP) and publicly available information from news media, social media, government sources, and NGO databases to develop a broader assessment of corporate social impact. Nevertheless, greater use of technology does not automatically result in more meaningful social evaluation. Digital datasets may exclude people with limited access to technology, while algorithms may reproduce biases present in the underlying data.

Experiences such as empowerment, participation, dignity, and social inclusion may also be difficult to represent through numerical indicators. Jayanthi et al. (2026) identify fragmented data standards, algorithmic bias, and uneven institutional capacity as significant challenges in AI-supported sustainability measurement. The present paper therefore approaches AI-assisted CSR evaluation through a social work perspective. Its central argument is that AI can strengthen evaluation when it is used alongside community participation, conventional research methods, and professional judgement. The purpose should not be to replace human evaluation with automated scoring, but to use technology to support a more inclusive, evidence-based, and context-sensitive understanding of CSR outcomes.

2.Objectives

The paper has three objectives:

1. To examine emerging applications of Artificial Intelligence in CSR evaluation.
2. To analyse the opportunities and ethical challenges associated with AI-assisted CSR evaluation.
3. To propose a community-centred framework integrating AI, stakeholder participation, and social work practice.

3. From Conventional CSR Evaluation to AI-Assisted Evaluation

CSR evaluation traditionally relies on programme records, expenditure statements, beneficiary counts, surveys, interviews, field observations, case studies, and reports from implementing organisations. These methods remain valuable because they provide direct information about programme implementation and community experiences. However, conventional approaches can become difficult when CSR programmes operate across several locations or generate large volumes of information. There may also be a tendency to depend heavily on information produced by the organisations implementing the programme. This can limit the inclusion of independent or community-level perspectives.

The literature reviewed for this paper reflects this concern. Kolekar et al. (2025) argue that traditional CSR measurement may be overly dependent on company-reported information and may not sufficiently capture real-time public or third-party perspectives. Their proposed NLP-based system attempts to address this limitation by examining information from multiple sources, including social media, news, government databases, and NGOs. AI can potentially assist evaluators in managing this growing volume of information. It can classify data, identify recurring themes, detect patterns, compare information across locations, and analyse large quantities of textual material. NLP is particularly relevant when stakeholder feedback is available in unstructured forms.

Smart technologies may also contribute to the collection of CSR-related information. Upreti et al. (2024) discuss the use of smart devices and the Internet of Things (IoT) in CSR initiatives in India and suggest that such technologies may improve the efficiency and monitoring of environmental and social interventions. The shift towards technology-supported evaluation should, however, be understood as an evolution rather than a replacement of conventional methods. AI can process information at a scale that may be difficult for human evaluators to manage manually, but interpreting that information continues to require human judgement.

4. Applications of Artificial Intelligence in CSR Evaluation**4.1 Data Analysis and Pattern Identification**

CSR initiatives generate information from beneficiary surveys, programme records, company reports, NGO documentation, government sources, and digital platforms. AI can help organise and analyse these different forms of information. For example, an organisation implementing similar livelihood programmes across several communities may find it difficult to compare thousands of individual records manually. AI-assisted analysis could help identify patterns in participation, service access, programme completion, and reported outcomes.

Kaleem et al. (2025) identify analytics and automation as important areas in the emerging relationship between AI and CSR. Such applications may reduce routine analytical work and allow evaluation teams

to devote more time to interpretation and community engagement. However, the quality of AI-generated results remains dependent on the quality of the data. AI cannot automatically correct incomplete or poorly collected information.

4.2 Natural Language Processing and Stakeholder Perspectives

NLP is particularly relevant to CSR evaluation because much social information exists in textual form. Beneficiary comments, NGO reports, news articles, public reviews, and social media discussions may contain useful information about perceptions of CSR programmes. Kolekar et al. (2025) propose an NLP-based system that extracts information from multiple public sources and converts aspects of corporate social impact into measurable indicators. This approach is potentially useful because it moves CSR evaluation beyond a single organisational perspective. At the same time, online information should not be treated as a complete representation of community opinion. People with limited digital access, low digital literacy, or poor connectivity may be absent from such datasets. Online sentiment analysis should therefore be combined with interviews, focus group discussions, community meetings, and field observations.

4.3 Continuous Monitoring

AI may support monitoring throughout the life of a CSR programme rather than only at the end of an intervention. If repeated complaints, declining participation, or service-delivery problems appear in incoming data, evaluators may be able to identify them at an earlier stage. This can support adaptive programme management. Rather than waiting until the final evaluation reveals a problem, organisations may have an opportunity to investigate the issue and make adjustments during implementation. However, the usefulness of continuous monitoring depends on the indicators selected and the quality of the information collected. A system that focuses only on easily measurable indicators may overlook less visible but equally important social changes.

4.4 Predictive Analytics

AI-based predictive analytics may help organisations identify possible future trends based on existing information. In CSR, this could potentially support decisions relating to resource allocation, programme continuation, beneficiary targeting, or areas requiring additional intervention. Kaleem et al. (2025) discuss AI-enabled risk profiling and ESG monitoring as emerging applications. Such tools may provide additional information for decision-making. Nevertheless, predictions concerning communities should be interpreted cautiously. Social conditions may change because of economic, cultural, environmental, political, or institutional factors. Historical patterns cannot always predict future community needs. AI-generated predictions should therefore support, rather than determine, decisions.

4.5 CSR and ESG Reporting

AI can also assist organisations in processing sustainability information, classifying indicators, preparing reports, and monitoring ESG-related information. Jayanthi et al. (2026) discuss the potential of AI to strengthen sustainability measurement and ESG disclosures while also identifying fragmented standards and algorithmic bias as significant barriers. Better reporting may contribute to transparency, but reporting quality should not be confused with social impact. An organisation may produce a sophisticated ESG

report while community-level outcomes remain uncertain. Evaluation should therefore connect reporting with evidence of actual change.

5. Opportunities of AI-Assisted CSR Evaluation

One of the clearest advantages of AI is its ability to process large volumes of information efficiently. CSR programmes involving multiple locations and large beneficiary groups can generate datasets that are difficult to analyse manually. AI may reduce routine processing and allow evaluators to devote more time to field-level interpretation. Shrivastava (2025) suggests that AI can improve CSR efficiency and reduce errors, while Kaleem et al. (2025) highlight the role of analytics and automation. AI can also bring together information from different sources. Company reports may be considered alongside NGO records, government information, news coverage, and stakeholder feedback. Such triangulation may provide a more balanced picture of CSR performance. This is particularly relevant in India, where concerns have been raised about uneven CSR implementation and the limitations of self-reporting. Ghorpade and Mandal (2025) emphasise the need for stronger independent impact evaluation within India's CSR system.

Continuous analysis may also help identify emerging problems during programme implementation. This can make CSR programmes more responsive and reduce the possibility that problems remain unnoticed until the final evaluation. AI-generated analysis can further provide additional evidence for decisions concerning programme modification, resource allocation, and future planning. However, decisions affecting communities should remain accountable to human evaluators and stakeholders. A strong evaluation system should also promote learning rather than simply produce a final score. By comparing information across projects, AI may identify recurring patterns. For example, if participation is consistently lower among a particular group, the pattern may indicate an accessibility issue. AI may identify the pattern, but field-level engagement is necessary to understand its causes.

6. Ethical Challenges and Limitations

6.1 Data Quality

AI systems depend on the quality of the information available to them. Incomplete, outdated, inconsistent, or poorly collected data can lead to unreliable conclusions. Jayanthi et al. (2026) highlight fragmented data standards as a challenge in AI-enabled sustainability assessment. CSR organisations therefore need reliable systems for collecting, verifying, storing, and updating information before introducing sophisticated AI tools.

6.2 Algorithmic Bias

AI systems may reproduce biases contained in their underlying data. If certain communities or groups are poorly represented, their needs may receive less attention in automated analysis. Shrivastava (2025) identifies algorithmic bias as an important concern associated with AI in CSR. Human review is therefore particularly important when AI-generated findings are used in decisions affecting vulnerable populations.

6.3 Privacy and Data Protection

CSR evaluation may involve personal information relating to income, health, education, employment, and household circumstances. Organisations must therefore consider informed consent, confidentiality, data security, access controls, and appropriate data retention. Collecting more data is not necessarily better.

Organisations should collect information that is relevant to the purpose of the evaluation and handle it responsibly.

6.4 Transparency

Some AI systems may produce findings that are difficult for ordinary stakeholders to understand. If a programme receives an AI-generated impact score, evaluators should be able to explain what information contributed to that assessment and what its limitations are. Technology should not become a substitute for accountability.

6.5 Digital Exclusion

An evaluation based heavily on online information may overlook people with limited digital access. Rural communities, older persons, low-income households, and other groups may be less visible in digital datasets. Upreti et al. (2024) demonstrate the growing relevance of smart technologies in CSR, but technological expansion should be accompanied by attention to access and inclusion.

6.6 Reducing Social Change to Numbers

Social change is multidimensional. Increased income may be an important outcome, but it may not necessarily indicate increased empowerment or social security. Similarly, a community programme may show modest measurable economic outcomes while strengthening participation and collective action. AI can assist with measurable indicators, but qualitative and participatory evidence remains necessary to understand the meaning of those outcomes.

6.7 Overdependence on Technology

There is a risk that organisations may assume AI-generated findings are automatically objective. They are not. AI systems are developed using human-selected data, indicators, categories, and assumptions. Therefore, the more important question is not simply whether AI can evaluate CSR, but under what conditions AI can contribute responsibly to CSR evaluation.

7. A Social Work Perspective on AI-Assisted CSR Evaluation

The inclusion of social work in AI-assisted CSR evaluation is important because CSR programmes ultimately operate within communities. Social work provides a framework for understanding people not simply as data points but as participants with experiences, rights, needs, and capacities. Social workers can contribute through needs assessments, interviews, field visits, focus groups, and participatory methods. These approaches can identify community priorities that may not appear in administrative or digital datasets. Community members should participate not only in programme implementation but also in evaluating whether an intervention has been useful to them. Social workers can facilitate spaces in which community members discuss benefits, problems, unintended consequences, and possible improvements.

In simple terms, AI can identify patterns, while communities can help explain what those patterns mean. For example, an AI system may identify declining participation in a CSR programme. The numerical trend alone does not explain why participation has declined. Social workers may discover that working hours, transport difficulties, family responsibilities, social norms, or other local circumstances are responsible. This illustrates why technological findings require contextual interpretation. Social workers can also identify people who may be missing from digital datasets. Their role may be particularly important when

working with marginalised communities, women, older persons, persons with disabilities, rural populations, and economically disadvantaged groups.

Social work principles relating to dignity, confidentiality, participation, social justice, and non-discrimination can contribute to responsible AI use. Social workers can question findings that conflict with field realities and draw attention to possible harms. CSR programmes commonly involve corporations, NGOs, government agencies, community organisations, and beneficiaries. Social workers can facilitate communication among these groups and help translate technical findings into accessible language. Thus, AI and social work should not be viewed as competing approaches. AI contributes analytical capacity, while social work contributes human understanding, contextual knowledge, ethical judgement, and participatory practice.

8. Proposed Community-Centred AI-Assisted CSR Evaluation Framework

Based on the literature reviewed, this paper proposes a five-stage framework.

Stage 1: Clear CSR Objectives

The process begins with clearly defined objectives, intended beneficiaries, expected outcomes, and indicators. AI cannot compensate for poorly defined programme goals.

Stage 2: Multiple Sources of Evidence

Evaluation should draw on different forms of evidence, including:

- CSR programme records
- Beneficiary surveys
- Interviews and focus groups
- NGO reports
- Government data
- Community feedback
- Company disclosures
- News and publicly available information
- Relevant digital data

This approach responds to concerns about over-reliance on company-generated information identified by Kolekar et al. (2025).

Stage 3: AI-Assisted Analysis

AI can support:

- Data classification
- Pattern identification
- Natural Language Processing
- Sentiment analysis
- Comparison across locations
- Continuous monitoring
- Predictive analysis
- Report preparation

The purpose is to assist evaluators in managing information, not to allow AI to independently decide whether a programme is successful.

Stage 4: Community and Professional Validation

This is the most important stage of the framework. AI-generated findings should be taken back to communities and reviewed by professionals.

Evaluators should ask:

- Does the finding reflect community experience?
- Which groups are missing from the data?
- What explains the identified pattern?
- Are there social or cultural factors that have not been captured?
- Do beneficiaries agree with the assessment?
- Are there unintended effects?

Social workers can facilitate this validation through field visits, interviews, focus groups, and stakeholder consultations.

Stage 5: Evidence-Based Programme Improvement

The final assessment should combine AI analysis, community feedback, field observations, and professional judgement. The findings can then inform decisions about continuing, modifying, expanding, or redesigning a CSR intervention.

The framework therefore creates a feedback cycle:

CSR Intervention → Clear Objectives → Multiple Sources of Evidence → AI-Assisted Analysis → Community and Professional Validation → CSR Impact Assessment → Programme Improvement → Feedback into the Next CSR Cycle

The model places different actors in complementary roles. AI provides analytical assistance; communities contribute lived experience; social workers provide professional and ethical interpretation; and organisations remain responsible for decisions and outcomes.

9. Recommendations

Based on the literature reviewed and the proposed framework, the following recommendations are suggested:

1. **Use AI as a support tool rather than a replacement for conventional evaluation.** Surveys, interviews, field visits, and participatory methods should continue to be used.
2. **Develop reliable CSR data standards.** Organisations should establish clear procedures for collecting, verifying, storing, and updating information.
3. **Include communities in evaluation.** Beneficiaries should have meaningful opportunities to provide feedback and participate in interpreting findings.
4. **Establish ethical safeguards.** Privacy, informed consent, data security, transparency, and algorithmic bias should be addressed before AI tools are deployed.
5. **Include social workers in evaluation teams.** Their community-based and professional expertise can help interpret AI findings within local contexts.

6. **Avoid over-reliance on automated scores.** Quantitative indicators should be combined with qualitative and participatory evidence.

7. **Use evaluation for learning.** CSR evaluation should inform future planning and programme improvement rather than functioning only as a compliance or reporting exercise.

10. Conclusion

AI is opening new possibilities for CSR evaluation by making it possible to process larger amounts of information, analyse diverse sources, identify patterns, support continuous monitoring, and contribute to evidence-informed decision-making. Recent literature demonstrates growing interest in the use of AI, NLP, smart technologies, analytics, and ESG-related systems within CSR and sustainability practice (Jayanthi et al., 2026; Kaleem et al., 2025; Kolekar et al., 2025; Upreti et al., 2024). At the same time, the introduction of AI does not resolve the longstanding challenges of CSR evaluation. Concerns relating to data quality, algorithmic bias, privacy, digital exclusion, fragmented standards, and the measurement of complex social outcomes remain important. Evidence from CSR research in India also suggests that greater expenditure or compliance does not necessarily translate into equally strong developmental outcomes (Ghorpade & Mandal, 2025).

A community-centred approach therefore appears more appropriate than a purely technology-driven model. AI can help evaluators manage information and identify patterns, but communities provide knowledge about their lived realities. Social workers can connect these two forms of knowledge through professional interpretation, ethical oversight, participation, and stakeholder engagement. The proposed framework seeks to shift CSR evaluation from a predominantly reporting-oriented exercise towards a process that combines data, technology, professional judgement, and community voice. Its contribution lies not in suggesting that AI can independently measure social impact, but in demonstrating how AI may be responsibly integrated into a broader evaluation process.

The framework remains conceptual and requires empirical testing. Future studies could apply it to different CSR sectors and community settings to examine whether AI-assisted evaluation, when combined with participatory and social work methods, can improve the quality, inclusiveness, and usefulness of CSR impact assessment. Ultimately, the success of AI in CSR evaluation should not be measured only by how much information it can process, but by whether it helps organisations understand communities better and make more responsible decisions.

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