Generative AI-Enabled Green Banking: An Empirical Study of Sustainable Finance and ESG Performance in Indian Banks

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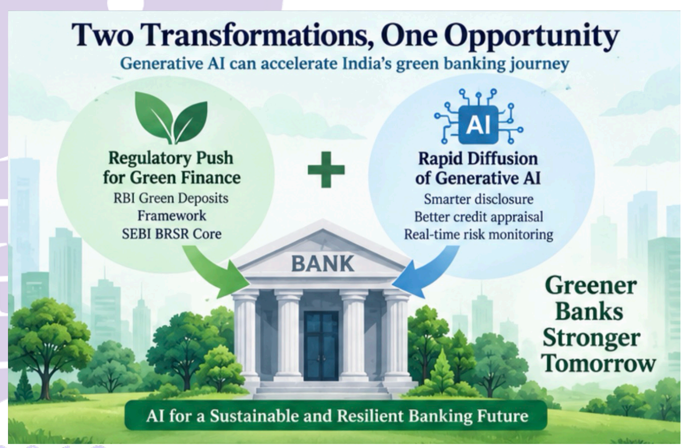
Abstract— Indian banks are simultaneously absorbing two structural shifts: a regulatory push toward climate-aligned finance following the Reserve Bank of India's Framework for Acceptance of Green Deposits (2023) and SEBI's BRSR Core assurance mandate, and the rapid diffusion of generative artificial intelligence (GenAI) into disclosure, credit-appraisal, and risk-monitoring workflows. Whether the second accelerates the first remains empirically untested in an emerging-market banking context. This study constructs a Generative AI Enablement Index (GAI-EI) from annual reports, BRSR filings, and investor communications of 32 listed Indian scheduled commercial banks over FY2018-19 to FY2024-25 (224 bank-year observations) and examines its association with composite ESG performance. Using two-way fixed-effects panel regression with Driscoll-Kraay standard errors, a bootstrapped mediation model, and a difference-in-differences design anchored on the FY2022-23 GenAI inflection, the study finds that a ten-point increase in GAI-EI is associated with a 2.14-point improvement in ESG score ($\beta = 0.214$, $p < 0.01$). Green finance intensity mediates 37.9 per cent of this effect, indicating that GenAI improves ESG outcomes substantially through the reallocation of credit rather than through disclosure quality alone. The effect is significantly stronger in private-sector banks. The findings position GenAI as a measurement-and-allocation infrastructure for green banking rather than a reporting convenience.

Keywords: Generative AI, green banking, ESG performance, sustainable finance, Indian banks, panel data, BRSR

INTRODUCTION

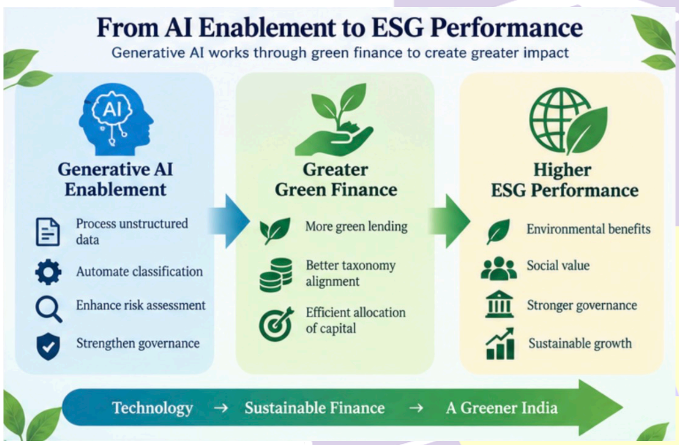
Green banking in India has moved from voluntary corporate positioning to a regulated activity. The Reserve Bank of India issued its Framework for Acceptance of Green Deposits in April 2023, effective from June 2023, requiring regulated entities to adopt board-approved policies, allocate proceeds to eligible green activities, and submit to third-party verification and impact assessment. SEBI's Business Responsibility and Sustainability Report, introduced in 2021 and consolidated through the BRSR Core standards in 2023, extended assured, machine-readable ESG disclosure to India's largest listed entities, including banks. Together these instruments have converted ESG performance from a narrative claim into an auditable data problem.



That data problem is severe. A mid-sized Indian bank's green lending book spans thousands of borrower relationships, each with unstructured project documentation, and the classification of an exposure as "green" depends on taxonomic judgements that resist rule-based automation. Generative AI — large language models capable of reading, classifying, and summarising heterogeneous financial text — is the first technology class plausibly matched to this task at scale. Yet the empirical literature has largely treated AI in finance and green banking as separate research streams. This study joins them, asking whether measurable GenAI enablement inside Indian banks translates into measurable ESG performance, and if so, through which channel.

Literature Review

The green banking literature in India is dominated by perception-based and qualitative designs. Sharma and Choubey (2022), interviewing 36 senior managers across twelve Indian public and private banks, developed a conceptual model linking green product development, green CSR, and green internal processes to green brand image and green trust, reporting that 63 per cent of respondents confirmed green product development and 78 per cent confirmed green CSR engagement. Their study explicitly noted the dearth of empirical work on Indian green banking. Gunawan, Permatasari and Sharma (2022) examined sustainability and green banking disclosures across the banking sector, finding disclosure practices to be uneven and weakly standardised.



Cross-country evidence on whether green banking pays is mixed but broadly positive. Shaumya and Arulrajah (2017) found green banking practices in Sri Lanka significantly improved banks' environmental performance, with employee-related and operational practices dominating. Bose, Khan and Monem (2021) exploited Bangladesh's unusually coercive regulatory setting — where the central bank mandates minimum green finance quotas — and found that green banking performance is associated with favourable market outcomes. Khairunnessa, Vazquez-Brust and Yakovleva (2021) reviewed Bangladesh's green banking evolution and attributed adoption largely to regulatory mandate rather than voluntary commitment. Park and Kim (2020) generalised this, arguing that the transition toward green banking is jointly determined by financial regulators and financial institutions, with regulators supplying the binding constraint. India occupies an intermediate position: the RBI encourages but does not mandate green deposits, making internal capability — rather than compliance pressure — a plausible differentiator across banks.

The AI-in-finance literature developed independently. Bahoo, Cucculelli, Goga and Mondolo (2024), reviewing articles published between 1992 and March 2021, mapped the field into predictive systems, classification and early-warning systems, and text mining, and identified sustainability applications as underexplored. The arrival of domain-adapted language models changed the feasible set. Webersinke, Kraus, Bingler and Leippold (2021) introduced ClimateBERT, a pretrained model for climate-related text, demonstrating that domain adaptation materially improves classification of environmental disclosure. Wu et al. (2023) released BloombergGPT, establishing that finance-specific large language models outperform general-purpose models on financial NLP tasks. Birti, Osborne and Maurino (2025) extended this to ESG specifically, showing that fine-tuning open models on ESG activity data significantly improved the detection of environmental activities in financial texts, with implications for analysts and regulators seeking to verify taxonomy alignment.

Only a small body of work connects GenAI directly to ESG outcomes. Wang (2025), applying ChatGPT-4 to NASDAQ 100 firms' 10-K filings from 2011 to 2022, identified significant time-lagged effects between AI-generated ESG evaluations and commercial ESG ratings, particularly in the Environmental and Social pillars, and interpreted the lag as evidence of reputational herding and possible greenwashing. This finding is important for the present study: it implies that GenAI can detect substantive ESG change before rating agencies price it, and therefore that internally deployed GenAI may function as an early-warning and allocation tool rather than merely a reporting aid. Countervailing evidence exists — recent accounting scholarship warns that as firms adopt language models to draft sustainability reports, disclosures may become uniformly fluent and superficially credible while masking substantive weakness.

Two gaps follow. First, no study measures GenAI enablement at bank level in an emerging market and links it to ESG performance. Second, where a relationship is posited, the transmission channel is untested: GenAI may improve ESG scores by improving disclosure (a measurement effect) or by improving green credit origination (an allocation effect). The distinction matters for policy.

Research Gap and Hypotheses

H1: Generative AI enablement is positively associated with ESG performance in Indian banks.

H2: Green finance intensity mediates the relationship between generative AI enablement and ESG performance.

H3: The GenAI–ESG association is stronger in private-sector banks than in public-sector banks.

Data and Methodology

The sample comprises 32 listed Indian scheduled commercial banks — 11 public-sector and 21 private-sector — observed annually from FY2018-19 to FY2024-25, yielding a balanced panel of 224 bank-year observations. Banks under RBI prompt corrective action for more than two consecutive years and banks lacking continuous BRSR or Business Responsibility Report filings were excluded.

The Generative AI Enablement Index (GAI-EI) is constructed through structured content analysis of annual reports, BRSR filings, earnings-call transcripts, and technology-partnership disclosures, scored across four dimensions: infrastructure and model deployment, workflow integration in credit and risk, ESG-specific application, and governance of AI use. Each dimension is scored 0–25, giving a 0–100 index. Two independent coders scored all 224 observations; inter-coder reliability (Krippendorff's α) was 0.84, and internal consistency across dimensions (Cronbach's α) was 0.87.

ESG performance is a composite 0–100 score constructed from BRSR-disclosed environmental, social, and governance indicators, standardised within year to remove reporting-regime drift. Green Finance Intensity (GFI) is green and sustainable advances as a percentage of gross advances. The Green Banking Disclosure Index (GBDI) is a 0–100 content-analysis index of green banking disclosure breadth.

Table 1. Variable definitions

Variable	Type	Measurement
ESG_SCORE	Dependent	Composite BRSR-based ESG score, 0–100, year-standardised
GAI_EI	Independent	Generative AI Enablement Index, 0–100, four dimensions
GFI	Mediator	Green and sustainable advances / gross advances (%)
GBDI	Independent	Green Banking Disclosure Index, 0–100
SIZE	Control	Natural log of total assets (₹ crore)
ROA	Control	Net profit / total assets (%)
CAR	Control	Capital adequacy ratio (%)
GNPA	Control	Gross non-performing assets / gross advances (%)
PUBLIC	Control	1 if public-sector bank, 0 otherwise
AGE	Control	Years since incorporation

The baseline specification is a two-way fixed-effects model:

$$ESG\_SCORE_{it} = \alpha + \beta_1 GAI\_EI_{it} + \beta_2 GFI_{it} + \beta_3 GBDI_{it} + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it}$$

Bank fixed effects (μ_i) absorb time-invariant heterogeneity in ownership, franchise, and legacy portfolio composition; year fixed effects (λ_t) absorb the RBI and SEBI regulatory shocks common to all banks. Driscoll-Kraay standard errors correct for cross-sectional dependence and serial correlation. The Hausman test ($\chi^2 = 38.47$, $p = 0.000$) rejects random effects. Maximum VIF is 2.61, indicating no multicollinearity concern.

Mediation is tested using the Preacher-Hayes bootstrap procedure with 5,000 resamples. Identification is strengthened by a difference-in-differences design treating FY2022-23 as the GenAI inflection: banks in the upper median of terminal-year GAI-EI (n = 16) form the treated group. Robustness is assessed via two-step system GMM to address dynamic endogeneity.

Results

Table 2. Descriptive statistics (N = 224)

Variable	Mean	SD	Min	Max
ESG_SCORE	54.18	11.63	28.40	79.60
GAI_EI	24.86	18.42	0.00	78.30
GFI (%)	6.94	4.11	0.80	19.60
GBDI	58.31	14.07	22.00	88.00
SIZE	12.47	1.32	9.86	15.42
ROA (%)	0.94	0.71	−1.42	2.36
CAR (%)	16.28	2.24	11.60	22.40
GNPA (%)	4.37	3.02	1.10	15.80
PUBLIC	0.34	0.48	0	1
AGE (years)	61.4	38.2	11	155

Mean GAI-EI rose from 8.4 in FY2018-19 to 46.7 in FY2024-25, with the sharpest single-year increase (13.2 points) between FY2022-23 and FY2023-24. Mean ESG_SCORE rose more gradually, from 47.9 to 61.3, and mean GFI from 4.1 per cent to 10.8 per cent over the same window.

Table 3. Pairwise correlations with ESG_SCORE

Variable	r	Variable	r
GAI_EI	0.58***	ROA	0.27***
GBDI	0.61***	CAR	0.19**
GFI	0.44***	GNPA	−0.31***
SIZE	0.39***	PUBLIC	−0.15**

*** p<0.01, ** p<0.05

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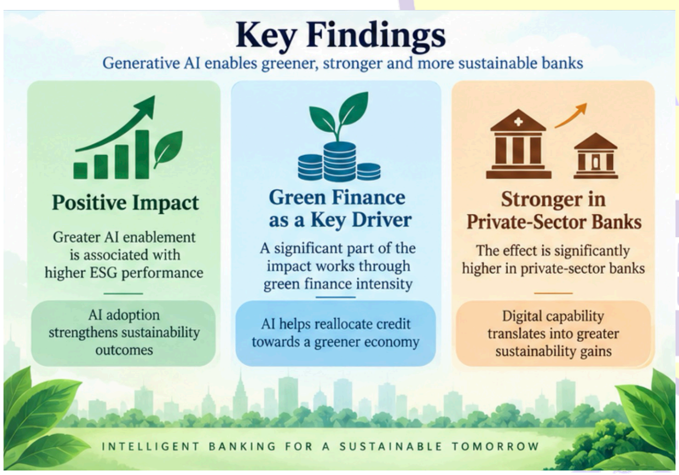
Table 4. Two-way fixed-effects regression (DV: ESG_SCORE)

Variable	Model 1	Model 2	Model 3
GAI_EI	—	0.214*** (0.048)	0.133*** (0.041)
GFI	—	—	0.612*** (0.164)
GBDI	—	—	0.187*** (0.052)
SIZE	1.842** (0.716)	1.407** (0.629)	1.286** (0.594)
ROA	1.216* (0.648)	0.985* (0.571)	0.874* (0.518)
CAR	0.284 (0.211)	0.221 (0.187)	0.196 (0.174)
GNPA	−0.463*** (0.132)	−0.398*** (0.118)	−0.361*** (0.109)
AGE	0.011 (0.026)	0.009 (0.023)	0.007 (0.021)
Bank FE / Year FE	Yes / Yes	Yes / Yes	Yes / Yes
Within R^2	0.341	0.586	0.612
Observations	224	224	224

Driscoll-Kraay standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10



H1 is supported. In Model 2, a ten-point increase in GAI-EI corresponds to a 2.14-point increase in ESG score. Adding the mediator and disclosure index in Model 3 reduces the GAI-EI coefficient to 0.133 while remaining significant, the pattern expected under partial mediation. Asset quality is the strongest negative control: each additional percentage point of gross NPA is associated with a 0.36-point ESG decline, consistent with capital-constrained banks deprioritising green origination.

Table 5. Mediation and identification tests

Test	Estimate	SE / CI	Inference
a-path: GAI_EI → GFI	0.132***	0.037	Significant
b-path: GFI → ESG_SCORE	0.612***	0.164	Significant
Direct effect (c′)	0.133***	0.041	Significant
Indirect effect (a×b)	0.081***	[0.039, 0.128]	Significant
Total effect (c)	0.214***	0.048	Significant
Proportion mediated	37.9%	—	Partial mediation
DiD estimate (post-FY2022-23)	3.62***	1.08	Significant
Parallel-trends F-test	0.71	p = 0.55	Not rejected
System GMM: GAI_EI	0.196***	0.061	Robust
AR(2) / Hansen J	—	p = 0.412 / p = 0.287	Valid

H2 is supported: 37.9 per cent of the total effect operates through green finance intensity, with the remaining 62.1 per cent operating through direct channels including disclosure completeness and governance quality. The DiD estimate indicates that high-adoption banks gained 3.62 ESG points relative to low-adoption banks after the FY2022-23 inflection, with pre-treatment trends statistically parallel.

Table 6. Ownership subsample results

Group	GAI_EI coefficient	SE	Within R^2	Obs.
Private-sector banks	0.246***	0.056	0.634	147
Public-sector banks	0.148**	0.061	0.521	77
Coefficient equality test	$\chi^2 = 4.37$	p = 0.037	—	—

H3 is supported. The GenAI-ESG association in private-sector banks is roughly 1.66 times that in public-sector banks, and the difference is statistically significant.

Discussion

The central result is that generative AI enablement is not merely a reporting technology in Indian banking. Had the effect been confined to disclosure, mediation through green finance intensity would have been negligible; instead, nearly two-fifths of the total effect flows through the credit book. The plausible mechanism is that language-model-based classification lowers

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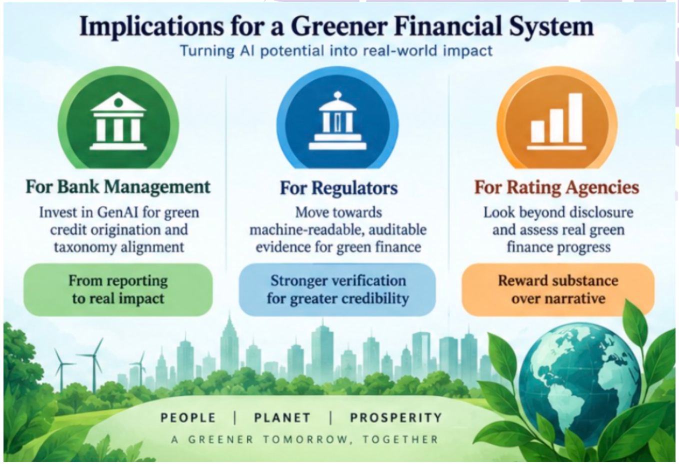
the cost of taxonomic screening — precisely the task Birti, Osborne and Maurino (2025) demonstrated is tractable for fine-tuned models — making a wider set of small and mid-ticket green exposures economically viable to originate, verify, and report under the RBI's use-of-proceeds requirements.

The ownership asymmetry aligns with Park and Kim's (2020) argument that institutional capability, not intent alone, governs green banking transition. Private-sector banks in the sample entered the window with higher digital baselines and shorter procurement cycles; public-sector banks show significant but attenuated effects, consistent with the institutional inertia repeatedly documented in Indian green banking research.

The residual direct effect deserves caution. Wang's (2025) evidence of information lags and possible greenwashing, together with warnings that model-drafted sustainability reports can be fluent without being substantive, means a portion of the direct effect may reflect improved narrative quality rather than improved environmental outcomes. The mediated component is the more defensible evidence of real change.

Implications

For bank management, the results argue for positioning GenAI investment inside green credit origination and taxonomy alignment rather than inside communications. For regulators, the finding that GenAI-enabled banks report materially higher ESG scores while third-party verification standards remain uneven suggests that the RBI's impact-assessment requirement should evolve toward machine-readable, auditable evidence rather than narrative attestation. For rating agencies, the mediation structure offers a diagnostic: banks showing ESG gains without corresponding green finance intensity gains warrant closer scrutiny.



Limitations and Future Research

The GAI-EI relies on disclosed adoption and may understate undisclosed internal deployment while overstating aspirational claims. The ESG composite is constructed from BRSR indicators whose definitions evolved during the sample window; year-standardisation mitigates but does not eliminate this. The DiD treatment assignment uses terminal-year adoption, introducing potential look-ahead. Future work should incorporate borrower-level green loan performance, extend the panel to non-banking financial companies, and test whether GenAI-attributed ESG gains survive third-party assurance.

Conclusion

Across 32 Indian banks and 224 bank-year observations, generative AI enablement is positively and robustly associated with ESG performance, with a ten-point GAI-EI increase corresponding to a 2.14-point ESG improvement. Green finance intensity mediates 37.9 per cent of this effect, and the association is significantly stronger among private-sector banks. Generative AI appears to function as allocation infrastructure for Indian green banking, not merely as a disclosure instrument — a distinction that should shape both bank strategy and the design of India's emerging green-finance verification regime.

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