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SUSTAINABLE FINANCE IN THE AGE OF AI AND GREEN BANKING ADOPTION AMONG INDIAN BANKING CUSTOMERS

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SUMMARY

The increasing use of artificial intelligence (AI) in banking opens up possibilities for advancing eco-friendly banking, however, there is little empirical evidence on the interaction between AI service features, environmental and functional perceptions, and customer adoption in India. The research analyzes the relationship of environmental concern, perceived usefulness, AI service convenience, and green perceived value to green banking adoption, using the attitude towards green banking as a mediating factor and the quality of AI adaptation as a moderating factor. Data were obtained from 516 users of digital bank services in India and was analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) technique with 5000 bootstrap resamples. It has been established that the quality of AI adaptation was the strongest predictor of green banking adoption ($\beta = 0.433$, $p < 0.001$). Environmental concern ($\beta = 0.228$, $p < 0.001$) and perceived usefulness ($\beta = 0.133$, $p = 0.013$) served as effective predictors of adoption, while the attitude towards green banking played an important positive role ($\beta = 0.232$, $p < 0.001$). AI service convenience had a significant impact on attitude ($\beta = 0.167$, $p = 0.003$) but not on adoption ($\beta = 0.035$, $p = 0.494$). Green perceived value was not significant for both attitude ($\beta = 0.028$, $p = 0.607$) and adoption ($\beta = -0.061$, $p = 0.195$). Attitude was a mediator in terms of the environmental concern ($\beta = 0.070$, $p = 0.001$), perceived usefulness ($\beta = 0.057$, $p = 0.007$), and AI service convenience ($\beta = 0.039$, $p = 0.025$). The moderating effect of AI adaptation quality was not significant ($\beta = 0.000$, $p = 0.990$). The findings indicate that functional usefulness, environmental concern, and AI-driven personalization are more influential adoption mechanisms than green value perceptions alone.

Key words: *green banking adoption, environmental concern, perceived usefulness, AI service convenience, green perceived value, AI personalization quality.*

INTRODUCTION

Climate change and increasing resource pressures have amplified the role of the financial sector from just seeking for profit to being environmentally sustainable. Sustainable finance is a process in which banks regard environmental issues when providing loans and assessing risks. Previous studies demonstrate that sustainable finance is rapidly growing nowadays, which can be noticed especially via a fast expansion of green reporting, green lending, and technology used for such services [3]. Green banking is an example of how this transition happens in banking, through such elements as paperless transactions, digital banking, green loans, and investments. The example of Indian banking sector shows that such practices can have an impact on consumer behavior but the acceptance of such practices depends on the level of awareness and involvement of the consumers [1][2].

Despite the benefits it brings, green banking adoption in India faces many challenges, such as regulatory confusion, lack of cooperation between institutions, and low level of awareness of customers [4]. At the same time, digitalization leads to transformation of banking thanks to AI technologies such as chatbots, process automation, prognosis, and recommendation services, thus enhancing accessibility and efficiency of banking [5][16][17]. But there is little evidence in terms of whether these technologies can increase green banking adoption among consumers and what are the key trends in this area in terms of emerging economies where digital banking develops much faster than awareness about sustainable finance. The interplay between ecological incentives and the attributes of service powered by AI that are relevant to consumers has not been sufficiently investigated.

Studies focused on green banking have taken into account environmental attitudes and cognitions based on the extended TPB framework. Technology adoption research is focused on adoption factors such as perception of utilization and convenience of service. AI research has furthering the understanding of personalization in finance and technology efficiency. However, the integrated model that illustrates the impact of environmental concern, perceived usefulness, AI service convenience, and green perceived value on the process of green banking adoption incorporating the role of attitude and AI personalization quality is still limited. The present study fills this gap providing an integration of behavioral and technology adoption theories.

This study aims to accomplish three objectives: (1) determine the impact of environmental concern, perception of usefulness, AI service convenience, and green perceived value on the attitude toward green banking; (2) analyze the effect of the above-mentioned factors and the attitude on the process of adoption; and (3) study the mediatory influence of attitude and moderatory impact of AI personalization quality on approaches to green banking. Green banking can only focus on the offering of green financial products and services that are user-facing digitally. It does not cover the processes that the banks themselves are implementing internally to be more eco-friendly [12][25].

Theoretical Background

The study is based on the theory of planned behaviour and technology adoption theories. The theory of planned behaviour assumes that attitude, subjective norms, and perceived behavioural control play a part in forming the behavioural intention, where attitude refers to a person's positive or negative assessment of a particular behavioural act. This study will take a closely related look at the concept of the attitude towards green banking as a mediating variable, with constructs related to environmental concern, perceived usefulness, AI service convenience, and perceived value taking their position as direct antecedents based on the belief system.

Another pillar for the theory used in this study comes from the technology adoption theory. The Technology Acceptance Model connects the relationship between perceived usefulness, attitude and behavioural intention. UTAUT and UTAUT2 emphasize such factors as performance expectancy, effort expectancy, facilitating conditions, convenience, and other factors related to consumers and technology [31]. All the aforementioned is pertinent, and because green banking can be considered as both sustainable and digital/technological choice it is useful to study it with the two previously discussed theories.

The framework used implies that attitude is seen as the mediation variable of environmental and technological beliefs and AI personalization quality is used as a boundary condition of the attitude-adoption relationship. Thus, one of the points the study will explore is whether the enhancement of a positive attitude into adoption can be reinforced by personalization or it can be treated as an independent factor.

The structure of the paper includes six sections. Section I, Introduction, outlines the research background, problem, research gap, objectives, significance, contributions, and scope of research. Section II, Theoretical Background and Literature Review, describes the theoretical underpinnings and presents research hypotheses. Section III, Conceptual Framework and Methodology, outlines the conceptual model, data collection method, measurement, sample, and PLS-SEM. Section IV, Results, describes demographic data, measurement, and validity of the findings, structural results, testing of the hypothesis, mediation and IPMA. Section V discusses the results and connects them to theoretical frameworks and research done before. Section VI is the conclusion and limitations of the study.

LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

Environmental Concern

Environmental concern reflects a customer's awareness of, and motivation to act on, ecological issues, and is consistently identified as a precursor of pro-sustainability financial choices. Behavioural-determinant research on Gen Z consumers finds that environmental awareness and financial literacy jointly shape sustainable consumption decisions, including the selection of green financial products [9]. Qualitative evidence from Indian banks similarly shows that customer-level environmental awareness is one of the strongest reported drivers behind uptake of green banking initiatives, alongside bank-level commitment [6]. Building on the TPB logic that beliefs about a behaviour's consequences shape attitude toward it, environmentally concerned customers should evaluate green banking more favourably and should also be more willing to use it directly.

Importantly, environmental concern in a banking context differs from environmental concern toward physical green products: because banking services are largely intangible, customers cannot directly observe the ecological consequences of, say, switching from paper statements to e-statements or choosing a green loan over a conventional one. Concern must therefore operate partly through trust that the bank's sustainability claims are credible - a condition that institutional governance and disclosure research suggests is itself variable across banks [12]. This makes environmental concern a necessary but not sufficient condition for adoption, reinforcing the case for modelling it alongside functional and technological antecedents rather than in isolation.

A further reason to expect a direct, and not merely attitude-mediated, effect of environmental concern on adoption is that some green banking behaviours - opting into paperless statements, for example - require little deliberation once a customer is environmentally motivated, and may therefore be adopted habitually rather than through a fully elaborated attitudinal evaluation. Modelling both a direct path (H1) and an attitude-mediated path (H5, tested jointly with H11) allows the empirical results to indicate which of these two behavioural routes better describes how environmental concern translates into use in the Indian retail banking sample.

H1: Environmental Concern has a Significant Positive Effect on Green Banking Adoption.

H5: Environmental Concern has a Significant Positive Effect on Attitude Toward Green Banking.

Perceived Usefulness

Perceived usefulness - the degree to which a customer believes a service improves their outcomes - remains the strongest and most replicated predictor across technology-adoption research. In the green banking context, usefulness extends beyond convenience to encompass service and environmental performance gains: banks whose green initiatives are perceived to genuinely improve environmental

outcomes also record stronger customer satisfaction and behavioural endorsement [10]. Conceptual work on green banking further argues that customer satisfaction, built on perceived functional benefit, is a necessary precondition for sustained usage rather than a by-product of it [8]. When customers see green banking as improving efficiency and outcomes, not merely as an ethical add-on, they are expected to form more favourable attitudes and be more likely to adopt it.

This functional framing is consistent with evidence from adjacent digital-banking domains: robotic process automation applied to financial-transaction reconciliation and compliance monitoring improves accuracy and turnaround time in ways that customers experience indirectly through faster, more reliable service, reinforcing the idea that usefulness in a banking setting is judged largely against tangible service-quality outcomes rather than abstract technological sophistication [7]. Perceived usefulness is therefore modelled here as both a direct predictor of adoption and an antecedent of attitude, reflecting its dual role as a functional evaluation and a belief input into the more general evaluative judgement that attitude represents.

A further consideration is that perceived usefulness in green banking is partly comparative: customers implicitly benchmark a green product or channel against the conventional alternative it replaces, so usefulness beliefs are unlikely to form in a vacuum. Where a green loan or paperless channel is perceived as no more useful than its conventional counterpart, purely environmental appeals would need to carry the full weight of the adoption decision.

H2: Perceived Usefulness has a Significant Positive Effect on Green Banking Adoption.

H6: Perceived Usefulness has a Significant Positive Effect on Attitude Toward Green Banking.

AI Service Convenience

AI service convenience captures the extent to which AI-enabled functions - chatbots, automated reconciliation, real-time support - reduce customer effort in banking interactions. Chatbot-based banking services have been shown to improve accessibility and responsiveness in online banking relative to traditional channels, and back-office AI tools such as robotic process automation improve the speed and reliability of transaction processing and compliance monitoring that customers experience as smoother service [7][20]. AI has likewise strengthened the security layer of digital banking: real-time, computational-intelligence-based fraud detection reduces friction and risk in electronic transactions, indirectly supporting customer confidence in digital and green channels alike [21]. Where AI reduces the effort and uncertainty involved in using digital banking, customers should form more favourable attitudes toward green banking channels and be more willing to use them.

AI service convenience is conceptually distinct from AI personalization quality, the moderator examined later in the model: convenience concerns the reduction of friction and effort in routine transactions, whereas personalization concerns the relevance and tailoring of recommendations and communications. The two constructs are expected to be positively associated in practice, since both stem from the same underlying AI infrastructure, but they are theorised to operate through different mechanisms - convenience primarily through effort-based evaluation consistent with UTAUT's effort-expectancy construct and personalization primarily through relevance-based evaluation - which is why they are modelled separately rather than as a single composite construct [31].

H3: AI Service Convenience has a Significant Positive Effect on Green Banking Adoption.

H7: AI Service Convenience has a Significant Positive Effect on Attitude Toward Green Banking.

Green Perceived Value

Green perceived value reflects a customer's overall assessment of the environmental and financial benefits of a service relative to its costs. Evidence from green-credit markets shows that environmentally oriented financial products can support bank profitability and stability, suggesting that value creation from green finance is real at the institutional level, and integrative fintech-CSR research links green-

finance value propositions to firm-level environmental sustainability performance [11][22][23]. Meta-analytic evidence on the sustainability-performance link is more mixed, however: financial performance gains from sustainability initiatives are real on average but vary considerably by context and measurement approach which suggests that value perceptions built primarily on environmental framing may not translate uniformly into individual customer attitudes or usage decisions in a services setting such as retail banking [24].

This ambiguity at the institutional level is expected to carry through to the customer level. Because green perceived value asks customers to weigh diffuse, long-horizon environmental benefits against immediate personal costs or effort, it is a cognitively harder judgement than perceived usefulness or AI service convenience, both of which are grounded in more immediate, personally experienced outcomes. The literature on sustainable-banking frameworks similarly notes that value-based sustainability appeals are only one of several institutional levers - alongside governance, disclosure and product design - available to banks, and are not consistently the most influential lever from the customer's perspective [25]. Green perceived value is nonetheless retained in the model as a direct and attitude-shaping antecedent, both because it is theoretically central to green-marketing frameworks and to allow the empirical results to speak to whether this institutional-level ambiguity is also visible in individual adoption behaviour.

A further complication is that green perceived value may be partly redundant with perceived usefulness and environmental concern once both are already in the model: if a customer already believes a green product is functionally useful and is already environmentally motivated, an additional 'value relative to cost' judgement may add comparatively little incremental explanatory power over and above those two more concrete beliefs. Retaining green perceived value as a distinct construct nonetheless allows this possibility to be tested directly rather than assumed.

H4: Green Perceived Value has a Significant Positive Effect on Green Banking Adoption.

H8: Green Perceived Value has a Significant Positive Effect on Attitude Toward Green Banking.

Attitude Toward Green Banking

Attitude - a customer's overall favourable or unfavourable evaluation of green banking - is the central mediating construct under TPB, and trust is a key input to it: research on bank advertising shows that both cognitive and affective trust shape how customers evaluate a bank's communicated offerings, including sustainability claims [13]. Conceptual modelling of green banking similarly proposes that customer attitude is the pivotal channel through which green banking practices translate into behavioural change, rather than practices affecting behaviour directly [2]. Consistent with this, attitude toward green banking is expected to convert the upstream beliefs examined above into adoption.

Modelling attitude as a mediator rather than simply as one predictor among several also has a practical payoff for banks: if the antecedents examined here operate mainly through attitude, then communication and product-design efforts that shift attitude directly - for example, transparent sustainability reporting or trust-building advertising - should have leverage over adoption even where a specific functional or environmental belief is hard to change quickly [13]. Where an antecedent instead retains a significant direct effect on adoption net of attitude, this signals that the belief operates through channels other than a general evaluative judgement, such as habitual use or perceived necessity, and warrants separate managerial attention.

Attitude is measured here as a global evaluative judgement toward green banking as a category, rather than toward any single green product, consistent with how TPB conceptualises attitude toward a defined behaviour. This global framing is appropriate given the study's aim of explaining adoption across the several green banking behaviours captured by the dependent construct (paperless transactions, green loans, sustainable investment products), but it also means the model is silent on whether attitude formation differs across these specific behaviours - a question left for the more granular, behaviour-specific future research discussed.

H9: Attitude Toward Green Banking has a Significant Positive Effect on Green Banking Adoption.

AI Personalization Quality

AI personalization quality denotes how accurately and relevantly an AI system tailors recommendations, communications and interfaces to an individual customer. Reviews of AI's role in sustainable finance argue that personalization is one of the primary mechanisms by which AI adds value to green financial services, by matching product recommendations to a customer's financial and environmental profile [14][15]. Broader innovation-management research frames AI-driven personalization as part of a wider organisational capability that supports sustainable-development goals when implemented with the right technical and process design [18][19]. Because personalization is theorised to strengthen the practical relevance customers assign to a recommendation, it is expected not only to influence adoption directly but also to condition how strongly a favourable attitude carries through into use.

The moderation hypothesis (H10) rests on a specific behavioural mechanism: personalization is expected to act as an amplifier that converts a favourable but latent attitude into actual use by surfacing the right green product, at the right time, in a way generic communication cannot. This mechanism is distinct from personalization's direct effect on adoption, which can occur even among customers who do not hold a strongly favourable attitude toward green banking per se - for instance, a customer might adopt a personalised green savings recommendation primarily because it is well-timed and relevant, independent of any broader environmental attitude. Testing both the direct and moderating pathways therefore allows the model to distinguish AI personalization as an independent adoption trigger from AI personalization as an attitude-strengthening mechanism.

Personalization quality is also likely to interact with customers' baseline digital literacy: a highly accurate recommendation delivered through an interface a customer finds hard to navigate is unlikely to convert into use regardless of how well it is targeted. While the present model does not decompose personalization quality by literacy segment, the sample's skew toward younger, more digitally active customers provides a reasonably favourable setting in which to detect a personalization effect if one exists, since digital-literacy barriers to acting on a personalised recommendation should be smaller in this population than in the Indian banking customer base as a whole.

H10: AI Personalization Quality Significantly Moderates the Relationship Between Attitude Toward Green Banking and Green Banking Adoption.

Green Banking Adoption

Green banking adoption is the customer's actual use of environmentally sustainable banking services - digital channels, paperless transactions, green loans and sustainable investment products. Institutional research shows that governance quality and disclosure practices shape how credible a bank's green offering appears to the market, which filters down to customer-level trust and uptake [12]. Adoption research on adjacent digital-banking innovations - neobanks, fintech-enabled financial inclusion, and IoT-enabled CRM - consistently finds that perceived benefit and ease of use, filtered through attitude, are the proximate drivers of uptake, while demographic and contextual factors such as digital-banking adoption stage in emerging economies play a moderating role [28][29][30]. Attitude toward green banking is therefore theorised as a mediating mechanism through which environmental concern, usefulness, convenience and value perceptions convert into adoption behaviour [26][27].

Treating adoption as the dependent construct in a mediation framework, rather than modelling intention as a proxy for behaviour as much of the technology-acceptance literature does, is a deliberate design choice [31]. Because the sample consists of customers already using at least one digital banking channel, green banking adoption in this study captures actual reported use of specific green features rather than a stated intention to use them in future, which reduces the well-documented intention-behaviour gap in pro-environmental research and gives the structural results a more direct behavioural interpretation.

The four antecedents are also expected to differ in how strongly they predict adoption once institutional credibility is accounted for. Governance-and-disclosure research suggests that customers' trust in a bank's green claims conditions how much weight they place on that bank's specific green products, which is one reason the present model expects environmental concern and green perceived value - both closely tied to how credible the bank's sustainability positioning appears - to behave differently from perceived usefulness and AI service convenience, which rest on more directly verifiable, functional experience rather than on trust in institutional claims [12].

H11: Attitude Toward Green Banking Mediates the Relationship Between Environmental Concern and Green Banking Adoption.

H12: Attitude Toward Green Banking Mediates the Relationship Between Perceived Usefulness and Green Banking Adoption.

H13: Attitude Toward Green Banking Mediates the Relationship Between AI Service Convenience and Green Banking Adoption.

H14: Attitude Toward Green Banking Mediates the Relationship Between Green Perceived Value and Green Banking Adoption.

Summary of Hypotheses

Table 1 consolidates the fourteen hypotheses developed above, distinguishing direct-effect, attitude-formation, mediation and moderation hypotheses, to give an overview of the full nomological network before the conceptual framework and measurement approach are presented.

Table 1. Summary of hypotheses

Hyp.	Relationship	Type
H1	Environmental concern → Green banking adoption	Direct effect
H2	Perceived usefulness → Green banking adoption	Direct effect
H3	AI service convenience → Green banking adoption	Direct effect
H4	Green perceived value → Green banking adoption	Direct effect
H5	Environmental concern → Attitude toward green banking	Direct effect
H6	Perceived usefulness → Attitude toward green banking	Direct effect
H7	AI service convenience → Attitude toward green banking	Direct effect
H8	Green perceived value → Attitude toward green banking	Direct effect
H9	Attitude toward green banking → Green banking adoption	Direct effect
H10	AI personalization quality × Attitude → Green banking adoption	Moderation
H11	Environmental concern → Attitude → Green banking adoption	Mediation
H12	Perceived usefulness → Attitude → Green banking adoption	Mediation
H13	AI service convenience → Attitude → Green banking adoption	Mediation
H14	Green perceived value → Attitude → Green banking adoption	Mediation

In table 1, the overview of the fourteen hypotheses is presented which is proposed to study the various direct, mediating, and moderating relationships among the constructs of the research. It is a summary of direct and indirect relationships tested against the research model.

According to existing literature, the adoption of green banking is influenced by environmental awareness, perceived usefulness, customer attitudes, and institutional conditions. On the other hand, the technology adoption literature emphasizes convenience, system quality, and perceived usefulness of system. Recent AI in banking studies indicate that personalization, automation, and intelligence may enhance customer experience and adoption of financial service by customers. However, it can be noted that these research domains developed independently from one another, and there is limited research available at customer level regarding the interaction of environmental motivation with AI-based service characteristics in the context of green banking adoption. Hence, the literature suggests the importance of developing a unified model that includes both sustainability-oriented and technology-based drivers

of adoption. In line with this gap, the present research examines environmental concern, perceived usefulness, AI service convenience and green perceived value as major predictors of green banking attitude mediated by attitude towards green banking and moderated by personalization quality in AI service.

CONCEPTUAL FRAMEWORK

The model outlined in figure 1 is summarised. It is proposed that environmental concern, perceived usefulness and AI service convenience and green perceived value influence attitude towards green banking (H5-H8) and have a direct effect on its adoption (H1-H4). Attitude is expected to influence adoption (H9) and mediate the relationships between the four antecedents and adoption (H11-H14). Lastly, AI personalization quality is placed as a boundary condition that moderates the attitude-adoption relationship (H10).

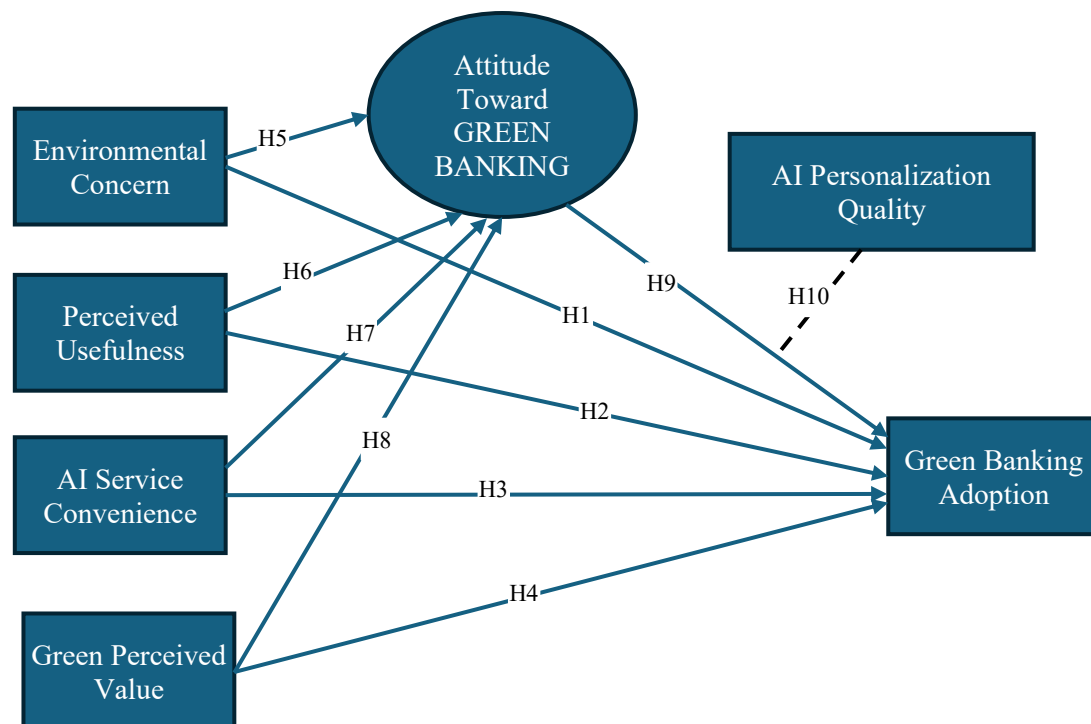


Figure 1. Conceptual framework

Table 2. Construct definitions and theoretical grounding

Construct	Working Definition	Theoretical Grounding
Environmental Concern (EC)	Customer's awareness of, and motivation to act on, ecological issues relevant to banking choices	TPB belief-attitude linkage; sustainable-consumption research [9]
AI Service Convenience (AISC)	Extent to which AI-enabled functions reduce customer effort in banking interactions	UTAUT effort expectancy [31];
Green Perceived Value (GPV)	Customer's overall assessment of environmental and financial benefit relative to cost	Green-marketing / sustainable-finance value literature [11][24]
Attitude toward Green Banking (ATGB)	Customer's overall favourable or unfavourable evaluation of green banking	TPB central mediator
AI Personalization Quality (AIPQ)	Accuracy and relevance with which AI tailors recommendations and interfaces	AI-in-sustainable-finance literature [14][15]
Green Banking Adoption (GBA)	Customer's actual use of environmentally sustainable banking services and products	Digital-banking adoption literature [26][27]

Table 2 is presenting the operational definitions of the seven constructs along with their theoretical base. The table also states how each of these constructs gets defined with the help of the integrated model of technology adoption and theory of planned behavior.

Methods

Data Collection and Sampling

A structured questionnaire implementing environmental concern, perceived usefulness, convenience of AI services, value of green, attitude towards green banking, quality of personalization of AI, and acceptance of green banking was distributed to retail banking customers in India who use at least one digital banking method (mobile banking, internet banking, or AI-enabled banking). Data were collected in three months from December 2025 to March 2026 using mail and social media for online distribution and in-person collection in bank offices or public venues for offline collection. The sample method used was convenience sampling, which was adapted to time restrictions as well as availability limitations. After issuing 550 questionnaires, 516 valid responses were collected, which provided enough data for Partial Least Squares Structural Equation Modelling (PLS-SEM).

Before starting the survey, respondents were screened to confirm that they have active accounts in an Indian bank, used a digital banking method within the last three months, and are at least 18 years old. Respondents who have not satisfied all three criteria have been excluded before beginning answering surveys.

Measurement, Pilot Study and Common Method Bias

The constructs were assessed utilizing a five-point Likert scale, where the measurement items were extracted from established scales in the literature on technology adoption and green marketing and adapted to fit in the context of digital banking in India and follow the principles of constructs based on theory of planned behaviors and technology adoption model as explained above. The constructs were operationalized with 3-5 reflective indicators each, and the wording of the items was reviewed by two subject matter academics for face validity before pilot testing was done with a sample of 50 active customers of digital banking. Piloting confirmed the clarity of the items and also generated the Cronbach's alpha of all constructs above the cut-off point of 0.70. To test for common method bias, general techniques of respondent anonymity, neutral wording, and the separation of outcome/predictor items were employed as well as a one-factor Harman test; the data revealed a one-factor explanation taking less than half of the total variance and showing that common method bias is not a problem.

Data Analysis

The SmartPLS 4 software was utilized to carry out a PLS-SEM analysis of the model, which is particularly effective in examining sophisticated analyses involving mediation and moderation since it does not require any limits imposed on the normality of the data distribution (unlike the CB-SEM approach). The measurement model was first validated in terms of the factors of indicator reliability and internal consistency; convergent and discriminant validity were evaluated subsequently. The structural model did not need to be evaluated until the measurement model was validated. Bootstrapping (with 5,000 resamples) was used to determine the significance of the various path estimates, and an Importance-Performance Analysis (IPA) of the importation variable was done as well.

IPA was specifically selected because calculating only the standard path coefficients does not provide oversights regarding the significance or relevance of the constructs already showing effective performance in the minds of the respondents. In the case with high coefficient constructs that have little room for future improvements, IPA provides assurance that the respective construct is overestimated as the influence of other constructs in the context of recommended managerial initiatives can be assessed more accurately.

Ethical Considerations

Everything that was done in relation to the inquiry was voluntary and anonymous; the subjects are told about the academic character of the initiative before filling in the questionnaire and can leave it at any moment, as there is no requirement to explain the decision in the process of the filling in. No interpersonal data was gathered and the information was processed in agreement with surveying methodologies that are used for consumer behaviour inquiries in banks.

RESULTS

Analysis Setup

Software Details. SmartPLS 4 was used for PLS-SEM, bootstrapping, mediation, moderation, and IPMA. Bootstrapping used 5,000 resamples.

Dataset Details. The final dataset contained 516 valid responses from Indian retail banking customers using at least one digital banking channel. Data were collected through online mail/social media and in-person collection. The seven model constructs were Environmental Concern (EC), Perceived Usefulness (PU), AI Service Convenience (AISC), Green Perceived Value (GPV), Attitude toward Green Banking (ATGB), AI Personalization Quality (AIPQ), and Green Banking Adoption (GBA).

Parameter Initialization. The main analysis settings are summarized in table 3.

Table 3. Parameter settings used for the analysis

Parameter	Setting
Software	SmartPLS 4
Scale	Five-point Likert scale
Indicators	3–5 reflective indicators per construct
Bootstrap resamples	5,000
Loading criterion	> 0.70
Cronbach's alpha / Composite Reliability	> 0.70
AVE	> 0.50
HTMT	< 0.90
VIF	< 3.3

Performance Metrics and Formulas

Cronbach's alpha:

$$\alpha = \left[\frac{k}{k-1} \right] \left[1 - \frac{\sum \sigma_i^2}{\sigma_t^2} \right] \quad (1)$$

Composite Reliability:

$$CR = \frac{(\sum \lambda_i)^2}{(\sum \lambda_i)^2 + \sum (1 - \lambda_i^2)} \quad (2)$$

Average Variance Extracted:

$$AVE = \frac{\sum \lambda_i^2}{n} \quad (3)$$

Where λ_i is the standardized loading. Reliability and convergent validity were assessed using Cronbach's alpha (Equation. 1), Composite Reliability (Equation. 2), and Average Variance Extracted (Equation. 3). Structural performance was evaluated using β , t , and p values, with $p < 0.05$ indicating significance.

Demographic Profile

Out of the 516 respondents, the male and female gender representation was almost equal (53.9% and 46.1%, respectively) and various categories of millennials and digital natives were targeted: respondents aged 26-35 and below 25 accounted for 36.0% and 27.5% respectively. Over one third of the respondents (43.4%) were postgraduates and around 38.4% were professionals while students accounted for 24.0 of respondents; 31.4% of respondents earned between ₹25,001 and ₹50,000 and combined banking experience over the years of 2 to 10 years accounted for 62.0%.

Table 4. Demographic profile of respondents (N = 516)

Category	Group	n	%
Gender	Male	278	53.90%
	Female	238	46.10%
Age	Below 25 years	142	27.50%
	26-35 years	186	36.00%
	36-45 years	112	21.70%
	Above 45 years	76	14.70%
Education	Postgraduate	224	43.40%
	Graduate / Other	292	56.60%
Occupation	Salaried employee	198	38.40%
	Student	124	24.00%
	Business / Self-employed	72	14.00%
Monthly Income	Others	122	23.60%
	Below ₹25,000	138	26.70%
	₹25,001-₹50,000	162	31.40%
	₹50,001-₹75,000	112	21.70%
Banking Experience	Above ₹75,000	104	20.20%
	Less than 2 years	96	18.60%
	2-5 years	174	33.70%
	6-10 years	146	28.30%
	More than 10 years	100	19.40%

Table 4 presents the demography of the 516 respondents which includes the data like age, sex, education, profession, monthly income, and banking expertise. The data shows that the respondents are young and tech-savvy users of the banking services.

In sum, the demographic profile suggests that the sample is composed mostly of technologically savvy but fairly inexperienced customers with a banking relationship that is still at an early to intermediate stage – a segment evaluating AI-based green banking features and capable of providing fair conclusions about the adoption of such services.

Measurement Model

The loadings of all the indicators were greater than 0.70. The values of Cronbach's alpha were within the range of 0.772 - 0.885 and values of composite reliability exceeded the value of 0.70 for each construct. Thus, it can be concluded that all measures are internally consistent. Average variance extracted was at the level of 0.608 - 0.753 and was greater than 0.50, proving the fact that the measures have convergent validity. The variance inflation factors for each measure indicated no multicollinearity issue at all, as they were less than 3.3.

Table 5. Measurement model summary

Construct	Alpha	ρ_a	ρ_c	AVE
AIPQ	0.804	0.807	0.885	0.719
AISC	0.772	0.795	0.867	0.686
ATGB	0.779	0.793	0.822	0.608
EC	0.885	0.885	0.916	0.685
GBA	0.785	0.785	0.875	0.699
GPV	0.839	0.884	0.901	0.753
PU	0.781	0.785	0.872	0.695

Table 5 contains the information regarding reliability and convergent validity of seven constructs. The values of Cronbach alpha, composite reliability, and AVE meet the required standards of the model confirming valid results.

The results suggest that the indicators of each construct explained significantly more variance in the construct in question than they do in the measurement error, and there was no other construct that was correlated so closely as to pose the danger of being indistinguishable at the level of the indicators. Hence, the reliability and convergent validity of the indicators are sufficient to move on to the structural path testing.

Discriminant Validity

Discriminant validity was established through the HTMT criterion (none of the values being equal to or above 0.90, with the largest value being AIPQ-GBA = 0.821) and through the Fornell-Larcker criterion (with the square root of each construct's AVE being greater than its correlation with other constructs).

Table 6. Fornell-Larcker criterion

	AIPQ	AISC	ATGB	EC	GBA	GPV	PU
AIPQ	0.848						
AISC	0.199	0.828					
ATGB	0.552	0.315	0.779				
EC	0.473	0.189	0.495	0.828			
GBA	0.653	0.165	0.566	0.510	0.836		
GPV	0.210	0.644	0.290	0.208	0.150	0.868	
PU	0.427	0.294	0.496	0.626	0.448	0.372	0.834

Table 6 presents the Fornell-Larcker indication of discriminant validity. The results show that the square root of AVE for the constructs exceeds their correlation values.

Even though the AIPQ-GBA linkage was lower than 0.90 it was still the most considerable association in the correlation chart thus suggesting existence of significant direct relationship between quality of personalization process in AI and its adoption; still, its HTMT remains within an appropriate range that is typically regarded as evidence of enough discriminant validity of reflective models in practice-based PLS-SEM research.

Structural Model and Hypothesis Testing

In this study, the structural model was assessed through the implementation of bootstrapping work (5,000 samples). It was evident that the most substantial direct factor affecting the adoption of green banking is the quality of personalization with the help of AI (AIPQ) ($\beta=0.433$, $p<0.001$); however, it was shown that AIPQ was not a significant moderator of the attitude-adoption connection ($\beta=0.000$, $p=0.990$), thus not confirming H10.

Table 7. Hypothesis testing (direct effects)

Hyp.	Relationship	β	t	p	Decision
H1	EC $\rightarrow$ GBA	0.228	4.163	<0.001	Accepted
H2	PU $\rightarrow$ GBA	0.133	2.473	0.013	Accepted
H3	AISC $\rightarrow$ GBA	0.035	0.684	0.494	Rejected
H4	GPV $\rightarrow$ GBA	-0.061	1.296	0.195	Rejected
H5	EC $\rightarrow$ ATGB	0.303	5.242	<0.001	Accepted
H6	PU $\rightarrow$ ATGB	0.247	4.165	<0.001	Accepted
H7	AISC $\rightarrow$ ATGB	0.167	3.001	0.003	Accepted
H8	GPV $\rightarrow$ ATGB	0.028	0.514	0.607	Rejected
H9	ATGB $\rightarrow$ GBA	0.232	4.008	<0.001	Accepted
H10	AIPQ $\times$ ATGB $\rightarrow$ GBA	0.000	0.012	0.990	Rejected

Furthermore, the decent level of concern regarding the environment appeared to be a predictor of both attitude ($B=0.303$, $p<0.001$) and adoption ($B=0.228$, $p<0.001$), thus confirming H1 and H5. The idea of usefulness was the predictor of both attitude ($\beta=0.247$, $p<0.001$) and adoption ($\beta=0.133$, $p=0.013$), thus proving H2 and H6. The convenience of AI services became the predictor of attitude ($\beta=0.167$, $p=0.003$, proving H7), but not of the adoption ($\beta=0.035$, $p=0.494$) due to the fact that H3 was not confirmed. Moreover, the value perceived as green did not impact the variables of attitude ($\beta=0.028$, $p=0.607$) or adoption ($\beta=-0.061$, $p=0.195$), thus disapproving H4 and H8. In contrast, attitude did prove to predict adoption ($\beta=0.232$, $p<0.001$), thus confirming H9.

Table 7 presents the analysis of results for the ten hypotheses related to the direct effects. The results of the research show that the variables environmental concern, perceived usefulness, and AI service convenience significantly influence the attitude toward technology along with the adoption of technology.

Mediation Analysis

Attitude toward green banking significantly mediated the effects of environmental concern ($\beta = 0.070$, $t = 3.195$, $p = 0.001$), perceived usefulness ($\beta = 0.057$, $t = 2.684$, $p = 0.007$), and AI service convenience ($\beta = 0.039$, $t = 2.246$, $p = 0.025$) on adoption, supporting H11, H12 and H13. Green perceived value showed no significant indirect effect ($\beta = 0.007$, $t = 0.498$, $p = 0.619$), so H14 is not supported. Attitude therefore operates as a genuine mediating mechanism for three of the four antecedents examined.

Table 8. Mediation analysis (specific indirect effects)

Hyp.	Path	β	t	p	Decision
H11	EC $\rightarrow$ ATGB $\rightarrow$ GBA	0.070	3.195	0.001	Accepted
H12	PU $\rightarrow$ ATGB $\rightarrow$ GBA	0.057	2.684	0.007	Accepted
H13	AISC $\rightarrow$ ATGB $\rightarrow$ GBA	0.039	2.246	0.025	Accepted
H14	GPV $\rightarrow$ ATGB $\rightarrow$ GBA	0.007	0.498	0.619	Rejected

Table 8 presents the analysis regarding the mediation effects of four antecedents of green banking adoption through attitude toward green banking. The findings suggest that attitude mediates between the environmental concern, perceived usefulness, and AI service convenience whereas there is no mediating effect of green perceived value.

The consistent pattern across H11-H13 - significant indirect effects with small-to-moderate coefficients - is typical of partial mediation in PLS-SEM applications, where a psychological construct such as attitude channel's part, but not all, of an antecedent's influence on behaviour. Combined with the direct-effect results in table 6, this indicates that environmental concern and perceived usefulness operate through both direct and attitude-mediated pathways to adoption, whereas AI service convenience operates only through attitude, and green perceived value operates through neither.

Importance-Performance Map Analysis (IPMA)

According to IPMA findings, both green perceived value (61.05) and AI service convenience (55.75) yield the highest performance metrics but have little structural significance which implies that there is a mismatch between performance and importance which banks have to be wary of when determining the investments. AI personalization quality (45.04), attitude (45.06), perceived usefulness (42.87), and environmental concern (41.08) emerge as the areas of high importance but low performance, thus highlighting them as subject to managerial enhancements.

The discovered mismatch between importance and performance for green perceived value and AI service convenience is a common observation for the IPMA: constructs that are low in structural significance can still score highly in perceived performance because respondents may simply judge their bank favorably on these constructs without realizing how those constructs contribute to adoption. Banks would be practically advised to abandon the investments in the constructs with high performance and low importance, such as the marketing of the presence of green perceived value, and concentrate on the dimensions with moderate performance and high importance (i.e. AI personalization quality, attitude, perceived usefulness, and environmental concern) as the areas of investments where meaningful improvements in adoption may take place.

It should be pointed out that AI service convenience and green perceived value are located in the same quadrants of the IPMA despite the fact that they characterize different constructs (technological and environmental-economic respectively). This indicates that both constructs are ineffective announcements and underlines the finding that consumers see their bank as satisfactory in both characteristics but are unable to use this information for better environmental banking utilization, which IPMA is developed to explore but that quantitative measures cannot reveal.

Performance Evaluation

Performance was evaluated using measurement reliability/validity, direct structural effects, and mediation effects. The results indicate acceptable measurement quality and significant effects for EC, PU, and ATGB, while AISC and GPV did not significantly predict adoption directly. The AIPQ moderation effect was also non-significant.

Table 9. Measurement performance

Construct	Alpha	CR	AVE
AIPQ	0.804	0.885	0.719
AISC	0.772	0.867	0.686
ATGB	0.779	0.822	0.608
EC	0.885	0.916	0.685
GBA	0.785	0.875	0.699
GPV	0.839	0.901	0.753
PU	0.781	0.872	0.695

Table 10. Structural performance

Path	β	t	p
EC $\rightarrow$ GBA	0.228	4.163	<0.001
PU $\rightarrow$ GBA	0.133	2.473	0.013
AISC $\rightarrow$ GBA	0.035	0.684	0.494
GPV $\rightarrow$ GBA	-0.061	1.296	0.195
ATGB $\rightarrow$ GBA	0.232	4.008	<0.001
AIPQ $\times$ ATGB $\rightarrow$ GBA	0.000	0.012	0.990

Table 11. Mediation performance

Mediated Path	β	t	p
EC $\rightarrow$ ATGB $\rightarrow$ GBA	0.070	3.195	0.001
PU $\rightarrow$ ATGB $\rightarrow$ GBA	0.057	2.684	0.007
AISC $\rightarrow$ ATGB $\rightarrow$ GBA	0.039	2.246	0.025
GPV $\rightarrow$ ATGB $\rightarrow$ GBA	0.007	0.498	0.619

The measurement model (Table 9) confirms reliability and convergent validity, with all Cronbach's alpha (0.772–0.885), Composite Reliability (0.822–0.916), and AVE (0.608–0.753) values exceeding standard thresholds (0.70 and 0.50, respectively). The structural model (Table 10) shows that ATGB ($\beta = 0.232$, $p < 0.001$), EC ($\beta = 0.228$, $p < 0.001$), and PU ($\beta = 0.133$, $p = 0.013$) significantly drive GBA, whereas AISC, GPV, and the AIPQ $\times$ ATGB interaction have no significant direct effect. Lastly, mediation analysis (Table 11) establishes that ATGB significantly mediates the paths from EC ($\beta = 0.070$, $p = 0.001$), PU ($\beta = 0.057$, $p = 0.007$), and AISC ($\beta = 0.039$, $p = 0.025$) to GBA, but does not mediate the GPV path ($\beta = 0.007$, $p = 0.619$).

Ablation Study

A conventional algorithmic ablation study is not applicable because the study uses a survey-based PLS-SEM model rather than a modular predictive algorithm. As a brief sensitivity check, direct and mediated paths were examined separately; EC and PU remained significant through both routes, whereas GPV remained non-significant.

DISCUSSION AND IMPLICATIONS

Discussion

The tremendous direct influence of AI personalization quality on adoption is in accordance with the larger AI-in-finance literature asserting that personalization represents an essential mechanism for value enhancement and coincides with findings derived from the UTAUT theory demonstrating that technological features are influential adoption drivers per se. At the same time, the lack of significance of its moderating influence indicates that personalization acts as an autonomous adoption trigger rather than being an accelerator of the existing attitude, which has not been mentioned before in the AI-banking literature. The reason for this is that personalization functions mainly due to the relevance-timing mechanism, which is about providing the right recommendation at the right time and thus ensures use irrespective of customer's earlier evaluation of the green banking domain, rather than through the slow belief-change.

The convenience of AI services had an impact on attitudes first but not on adoption directly, which is consistent with works stating that convenience-related AI features, like chatbots primarily deal with delivering positive service experience rather than pushing people to use AI-based services immediately; the involvement of the attitude in the process of adoption is emphasized by mediation results (H13). This is an important conceptual distinction of AI personalization quality from the AI service convenience since, although both are AI-related, the former works as an independent behaviour trigger and the latter acts as a conventional belief input to attitudes according to the TPB theory. Environmental consciousness and perceived effectiveness made an impact on both attitudes and adoption in accordance. The dual importance of the two constructs, being both the direct impact and the impact based on the change of attitude, indicates that most likely the number of two variables are the strongest predictors in the model and replicates the effect found in the literature on green banks and the literature on technology acceptance. The insignificant impact of green perceived value coincides with the disproportional results regarding sustainability and performance found in the meta-analyses. The most probable explanation of this is connected with the fact that customer preferences of the services provided by banks are influenced by functional and technical features rather than by sustainability framing. This corresponds with the conclusions made in the literature on sustainable banking that state that appeal based on values is not the only one used in banking, and probably not the most effective. The fact that green perceived value is not statistically significant does not mean that people do not take sustainability into account when

making the decisions on banking services but rather shows that the understanding of green perceived value as used in this paper is not effective enough to influence the decision-making process.

To summarize, the significant role of the attitude in mediating three out of four antecedents presents evidence in support of TPB assumption that the attitude is a primary construct connecting beliefs and behavior and that the general trend of very powerful technological and functional influences combined with a minimal impact of pure environmental aspect is consistent with the findings of research into adoption of digital banking in other developing countries where the advantages of using such services are more important to people than their sustainability effect. The results of the research describing these findings and showing that customers' perception of the effectiveness of the adoption process is more important than any resistance also corresponds to the previously reported facts in frontiers of neobanking and IoT-enabled CRM sphere showing that while demographic aspects influence personalization process and adoption, the functional and technological pathway to adoption described in this research is present in other spheres of experience of Indian customers having access to new financial services. To sum up, ten results found with the help of direct effects analysis and four mediation results provide evidence of the way green banking adoption takes place in this study: two strong drivers connected with dual pathways of functioning: environmental concern and perceived usefulness of green banking; one driver connected only with attitude: AI service convenience; one driver that does not influence attitude but influences behavior significantly: AI personalization quality; and one driver that does not affect either attitude or behavior: green perceived value.

Implications

Theoretical Outcomes

The research incorporates the principle-driven framework of TPB with the notions of technology application to clarify the environmental digital technology significance in boosting green banking uptake. The study also enhances the literature on AI usage in finance by illustrating that the quality of AI customization can be considered as the direct determinant of behavior instead of just an influencer of attitude strength, qualifying the previous assumption of green marketing that environmental value perception can be explicitly linked with uptake as a part of green banking. Additionally, by distinguishing AI service utility and AI customization quality, the research suggests a more differentiated understanding of the concept of 'AI-enabled service quality' in comparison to what is presented in the literature on AI in banking. The research contributes to the understanding of mediation in green banking by investigating the actual mediating role of attitudes instead of presuming it. Unlike the conventional approach claiming that if there are antecedents the attitude will certainly mediate their relationships, the study provides evidence that there are exceptions – in its case three antecedents mediated whereas one did not.

Managerial Implications

The significant influence of AI personalization on adoption must compel banks to invest in this strategy, wherein they provide timely and relevant financial advice to customers in consideration of their needs. While banks should emphasize the efficiency and cost-saving benefits related to green banking, they should also pay attention to its perceived usefulness, since these aspects lead to better adoption and attitudes. Though convenience of AI service has an indirect influence, banks should still maintain investments in cost-effective AI solutions, as the positive effect is recognized in the attitude and not so much via use as such. Finally, while green perceived value does not lead to significant adoption, sustainability communication must be associated with practical customer benefits, rather than deployed as a standalone appeal. The IPMA results serve as a useful prioritization instrument for banking sustainability practices: while investments must be made evenly across all seven constructs, banks must consider the high importance and moderate performance of AI personalization quality, as well as approach the matters of attitude, perceived usefulness, and environmental concern before choosing to make investments in the low significance but high-performance green perceived value and AI service convenience. From a practical standpoint, the findings suggest a sequence that requires banks with limited budget possibilities to make AI personalization capabilities. AI personalization capabilities are

linked with the necessary data infrastructure and recommendations used to match individual green products for specific customers, and its significance being paramount is unquestionable.

Policy Implications

Regulators and industry bodies that want to accelerate the development of green banking should realize that policies focusing exclusively on environmental information or green labeling may have less impact on consumer adoption without any guarantees of technology and functional quality. Regulatory frameworks should prompt banks to invest in AI personalization and reliable service solutions through legislation that guarantees responsible use of AI in customer service banking to help multiply green banking. Besides, industry associations should provide financial literacy initiatives that can strengthen the path from environmental concern to attitude and adoption, as this path proved to have a significant impact on both aspects according to the current data.

CONCLUSION

The research indicates that AI personalization excellence, perceived usefulness, attitude toward green banking and environmental concern are the four most significant factors which foster green banking adoption among Indian consumers, with the attitude mediating most of the listed relationships and AI personalization excellence also having a considerable predictive power. The notion of green perceived value and importance of personalization as a moderator were not confirmed, which implies that customers currently consider functional and technical aspects more important than environmental framing on its own. The outcomes extend TPB and technology adoption theory to the context of AI-enabled green banking and provide banks with a clear actionable recommendation: combine the use of AI-based personalization with fundamental functional and sustainable benefits communicated in a clear way so as to enhance green banking uptake in developing countries like India. In general, the findings indicate that in markets like India, the future of green banking is going to depend not so much on the effectiveness of green messaging as on the degree of its implementation within the framework of AI-driven functional digital experience. It is expected that as AI capabilities grow in banking, the distinction between digital banking and green banking will tend to disappear, which makes the combined behavioral and technological framework developed in the current research increasingly relevant for both researchers and practitioners monitoring sustainable finance in developing countries. In particular, for Indian banks, the findings lay out the practical roadmap: treat AI personalization not as optional addition but as necessary infrastructure, make further investments in simple AI solutions even if their benefits are indirect, continue stressing the importance of environmental concerns and usefulness through simultaneous functional and sustainable messaging and think anew about how to communicate green perceived value in light of its historically low role in the current model. Those banks that follow this roadmap will be able to see the increase in the adoption of green banking not because customers have become more eco-minded in theory but because they have the necessary experience of using effectively AI-based digital platforms for using the green products.

REFERENCES

- [1] Jain A, Behera B, Kochhar K. Customer adoption of green banking: an extended theory of planned behavior. *Management Decision*. 2026 Jan 15;64(1):52-73. <https://doi.org/10.1108/MD-06-2024-1438>
- [2] Jain A, Yadav P, Kochhar K. Do Green Banking Practices Change Customers' Attitudes and Behavior: A Conceptual Model. *Indian Journal of Finance*. 2024 Apr 1:25-43. <https://doi.org/10.17010/ijf/2024/v18i4/173725>
- [3] Venkatesh V, Davis FD. A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management science*. 2000 Feb;46(2):186-204. <https://doi.org/10.1287/mnsc.46.2.186.11926>
- [4] Chandran R, Chandran MS, Achuthan K, Sahib PR. Theoretical perspectives on green banking adoption in India: regulatory uncertainty, institutional barriers, and policy solutions. *Discover Sustainability*. 2025 Jul 1;6(1):581. <https://doi.org/10.1007/s43621-025-01406-3>
- [5] Venkatesh V, Thong JY, Xu X. Consumer acceptance and use of information technology: Extending the Unified Theory of Acceptance and Use of Technology1. *MIS quarterly*. 2012 Mar 1;36(1):157-78. <https://doi.org/10.2307/41410412>
- [6] Sharma M, Choubey A. Green banking initiatives: a qualitative study on Indian banking sector. *Environment, Development and Sustainability*. 2022 Jan;24(1):293-319. <https://doi.org/10.1007/s10668-021-01426-9>

- [7] Lee, S., & Vincent, C. (2021). Analysis and evaluation of the theory of planned behavior. *Advances in Nursing Science*, 44(4), E127-E140. <https://doi.org/10.1097/ANS.0000000000000369>
- [8] Herath HM, Herath HM. Impact of Green banking initiatives on customer satisfaction: A conceptual model of customer satisfaction on green banking. *Journal of Business and Management*. 2019 Feb;1(21):24-35. <https://doi.org/10.9790/487X-2101032435>
- [9] Farzin M, Sadeghi M, Yahyayi Kharkeshi F, Ruholahpur H, Fattahi M. Extending UTAUT2 in M-banking adoption and actual use behavior: does WOM communication matter?. *Asian Journal of Economics and Banking*. 2021 Aug 11;5(2):136-57. <https://doi.org/10.1108/AJEB-10-2020-0085>
- [10] Shaumya K, Arulrajah A. The impact of green banking practices on bank's environmental performance: Evidence from Sri Lanka. *Journal of Finance and Bank Management*. 2017 Jun;5(1):77-90. <https://doi.org/doi:10.15640/jfbm.v5n1a7>
- [11] Sutrisno S, Widarjono A, Hakim A. The role of green credit in bank profitability and stability: a case study on green banking in Indonesia. *Risks*. 2024 Dec 10;12(12):198. <https://doi.org/10.3390/risks12120198>
- [12] Bose S, Khan HZ, Rashid A, Islam S. What drives green banking disclosure? An institutional and corporate governance perspective. *Asia Pacific Journal of Management*. 2018 Jun;35(2):501-27. <https://doi.org/10.1007/s10490-017-9528-x>
- [13] Bilisbekov N, Sarfo C, Dandis A, Eid M. Linking bank advertising to customer attitudes: The role of cognitive and affective trust. *Management science letters*. 2021;11(4):1083-92. <https://doi.org/10.5267/j.msl.2020.11.031>
- [14] Vyas AA, Suganthiya MS. Impact of artificial intelligence on sustainable finance. *ShodhAI: Journal of Artificial Intelligence*. 2025 Dec 1;2(2):42-7. <https://doi.org/10.29121/shodhai.v2.i2.2025.58>
- [15] Jha SK, Kushwah N. Artificial Intelligence (AI) in Sustainable Finance and Green Banking. *South India Journal of Social Sciences*. 2026 Jun 30;24(3):147-51. <https://doi.org/10.62656/SIJSS.v24i3.2420>
- [16] Narang A, Vashisht P, Bajaj SB. Artificial intelligence in banking and finance. *International Journal of Innovative Research in Computer Science and Technology*. 2024 Mar;12(2):130-4. <https://doi.org/10.55524/ijircst.2024.12.2.23>
- [17] Kumar A, Srivastava A, Gupta PK. Banking 4.0: The era of artificial intelligence-based fintech. *Strategic Change*. 2022 Nov;31(6):591-601. <https://doi.org/10.1002/jsc.2526>
- [18] Kulkov I, Kulkova J, Rohrbeck R, Menvielle L, Kaartemo V, Makkonen H. Artificial intelligence-driven sustainable development: Examining organizational, technical, and processing approaches to achieving global goals. *Sustainable Development*. 2024 Jun;32(3):2253-67. <https://doi.org/10.1002/sd.2773>
- [19] Gujrati P, Biradar J. Application of artificial intelligence in banking and finance: Bibliometric review and emerging research agenda. *Indian Journal of Computer Science*. 2023 Oct 31:27-37. <https://doi.org/10.17010/ijcs/2023/v8/i5/173322>
- [20] Doherty D, Curran K. Chatbots for online banking services. In *Web Intelligence 2019 Dec 2* (Vol. 17, No. 4, pp. 327-342). Sage UK: London, England: SAGE Publications. <https://doi.org/10.3233/WEB-190422>
- [21] Quah JT, Sriganesh M. Real-time credit card fraud detection using computational intelligence. *Expert systems with applications*. 2008 Nov 1;35(4):1721-32. <https://doi.org/10.1016/j.eswa.2007.08.093>
- [22] Schwendner P, Posth JA. Trends in AI4ESG: AI for sustainable finance and ESG technology. *Frontiers in artificial intelligence*. 2024 Jun 25; 7:1448045. <https://doi.org/10.3389/frai.2024.1448045>
- [23] Yuan X. Integrating Fintech, CSR, and green finance: impacts on financial and environmental performance in China. *Humanities and Social Sciences Communications*. 2025 Jul 12;12(1):1072. <https://doi.org/10.1057/s41599-025-05064-8>
- [24] Atz U, Van Holt T, Liu ZZ, Bruno CC. Does sustainability generate better financial performance? review, meta-analysis, and propositions. *Journal of Sustainable Finance & Investment*. 2023 Jan 2;13(1):802-25. <https://doi.org/10.1080/20430795.2022.2106934>
- [25] Aracil E, Nájera-Sánchez JJ, Forcadell FJ. Sustainable banking: A literature review and integrative framework. *Finance Research Letters*. 2021 Oct 1; 42:101932. <https://doi.org/10.1016/j.frl.2021.101932>
- [26] Bhatnagar P, Rajesh A, Misra R. Neobank adoption: integrating the information systems effectiveness framework with the innovation resistance model. *Management Decision*. 2024 Dec 5;62(10):3315-52. <https://doi.org/10.1108/MD-06-2023-0977>
- [27] Asif M, Khan MN, Tiwari S, Wani SK, Alam F. The impact of fintech and digital financial services on financial inclusion in India. *Journal of Risk and Financial Management*. 2023 Feb;16(2):122. <https://doi.org/10.3390/jrfm16020122>
- [28] Acosta-Prado JC, Rojas Rincón JS, Mejía Martínez AM, Riveros Tarazona AR. Trends in the literature about the adoption of digital banking in emerging economies: A bibliometric analysis. *Journal of Risk and Financial Management*. 2024 Nov 29;17(12):545. <https://doi.org/10.3390/jrfm17120545>
- [29] Alnemer HA. Determinants of digital banking adoption in the Kingdom of Saudi Arabia: A technology acceptance model approach. *Digital Business*. 2022 Jan 1;2(2):100037. <https://doi.org/10.1016/j.digbus.2022.100037>

- [30] Bajaj P, Anwar I, Yahya AT, Saleem I. Factors influencing adoption of IoT and its impact on CRM in banks: examining the moderating role of gender, age, and bank ownership type. *Human Behavior and Emerging Technologies*. 2023;2023(1):5571508. <https://doi.org/10.1155/2023/5571508>
- [31] Venkatesh V, Morris MG, Davis GB, Davis FD. User acceptance of information technology: Toward a unified view1. *MIS quarterly*. 2003 Sep 1;27(3):425-78.